Nonbanks, Banks, and Monetary Policy: U.S. Loan-Level Evidence since the 1990s*

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Abstract

We analyze the effects of monetary policy on nonbank and bank credit supply to firms and households, in particular the associated real effects and the distribution of risk. For identification, we use exhaustive loan-level data since the 1990s and Gertler-Karadi (2015) monetary policy shocks. First, different from the literature showing that low monetary policy rates increase risk-taking in bank loans, we find that higher monetary policy rates lead to an expansion of credit supply and more risk-taking by nonbank lenders. During monetary contractions, credit supply for corporates, mortgages, and consumers shifts from regulated banks to less regulated, more fragile nonbanks. Moreover, this shift is more pronounced for ex-ante riskier borrowers. Second, nonbanks reduce the effectiveness of the bank lending channel of monetary policy at the loan-level. However, this reduction varies substantially by borrower type. Total credit and real effects are largely neutralized in consumer loans and the associated consumption, but not in corporate loans and investment.

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1 Introduction

The structure of financial markets in general, and credit markets in particular, has dramatically changed over the recent decades. Nonbank credit intermediaries (e.g. hedge funds, investment funds, private equity, and fintech lenders)that are less regulated and supervised than banksnow have a significantly larger presence. While a large literature shows that banks cut their supply of credit and reduce risk taking in response to a tightening of monetary policy, it is unclear whether, and how, nonbank lenders affect monetary policy transmission. Do nonbank lenders attenuate or increase the potency of the bank lending channel of monetary policy? And how does nonbank lenders risk-taking respond to monetary policy?

Several theories suggest that banks are central in the credit supply reduction after a monetary policy tightening. Tighter monetary policy reduces credit supply via a reduction in bank reserves (Kashyap and Stein 1995, 2000; Stein 1998) and deposit outflows (Drechsler, Savov, and Schnabl 2017). However, deposits leaving the banking sector may be shifted to nonbanks (Xiao 2017), potentially resulting in an expansion of nonbank lending. Under this theoretical channel, substitution between bank and nonbank lending would considerably attenuate the bank lending channel of monetary policy. An alternative view, as formulated by a then Governor of the Federal Reserve, Jeremy Stein, is that monetary policy (relative to prudential policy) "gets in all the cracks" by acting directly on market rates and spreads (Stein 2013).[1] In other words, a tightening of monetary policy negatively affects the funding conditions of *all* financial intermediaries that borrow short-term, potentially limiting nonbanks' ability to substitute for bank credit.[2]

Prior studies also suggest that low monetary policy rates, or expansive monetary policy more generally, increase banks risk-taking substantially, thereby creating a risk-taking

[1]See also the Jackson Hole paper by Greenwood, Hanson, and Stein (2016).

[2]Bernanke (2007), following Bernanke, Gertler, and Gilchrist (1999), applies the financial accelerator theory to financial intermediaries.

channel of monetary policy (Adrian and Shin 2010; Allen and Rogoff 2011; Borio and Zhu 2012; Diamond and Rajan 2012). However, Rajan's (2005) Jackson Hole Paper argues that nonbank intermediaries are also affected by low monetary policy rates. Importantly, the effect of monetary policy on nonbanks risk-taking in loans has not been studied.

Our main contribution is to document that monetary policy differently affects banks' and nonbanks' credit supply and risk-taking. For identification, we exploit U.S. loan-level data for both firms and households since the 1990s, where we know whether the lender is a bank or a nonbank, in conjunction with monetary policy shocks from Gertler and Karadi (2015). We find that contractionary monetary policy shifts both, credit supply and funding liquidity from banks to nonbanks. Nonbank credit supply relatively expands, demand factors matter, and effects are stronger for ex-ante riskier loans. Despite that monetary policy affects all intermediaries by impacting market rates, our results show that nonbank lenders significantly attenuate *both*, the bank lending and bank risk-taking channels of monetary policy. However, the credit supply and associated real effect effects differ substantially across markets. For the risk-taking channel, we find that nonbanks take more risk in all markets when monetary policy tightens, indicating that monetary policy affects the distribution of credit risk across different financial intermediaries but not necessarily the economy-wide level of risk taking. Moreover, total credit and real effects are largely neutralized in consumer loans and the associated consumption, but not in corporate loans and investment.

We start our analysis of the effects of monetary policy on nonbank credit supply with the syndicated corporate loan market. Using data from Thomson Reuters LPC DealScan (DealScan), we identify nonbank lenders and originations of new syndicated loans. The main advantage of studying syndicated loans is that they are originated by multiple lenders. This feature allows us to control for firm-level credit demand (and other unobserved firm fundamentals) and therefore to identify the effects of monetary policy by comparing credit supply of bank and nonbank lenders to the same borrower in the same quarter.

Using this within-borrower variation in credit (i.e., firm-time fixed effects), we find that nonbanks expand credit supply to US corporate borrowers after a monetary contraction relative to their bank peers. Nonbank credit supply increases by 12 percent relative to bank credit supply after a one standard deviation increase in the monetary policy measure attenuating the bank lending channel. Moreover, the increases in credit supply are larger for ex-ante riskier (non-investment grade) firms.

The substitution from bank to nonbank credit, however, is only partial. Our results suggest that one key factor explaining the limited substitution is that the overall reduction in credit volume is partly driven by demand factors rather than by a reduction in credit supply. Moreover, substitution could also be limited by the nature of the syndication process, which relies heavily on soft information and therefore involves high switching costs for borrowers and lenders.[3]

We therefore study whether borrowers that have established relationships with nonbank lenders in the past, which reduces informational and other borrower-lender frictions, are better able to access credit when monetary policy tightens. We find that borrowers that have borrowed from nonbanks in the past experience a larger relative expansion in credit following monetary contractions, and that this is associated with a reduction in liquid asset holdings and an increase in fixed assets (investment). These findings suggest that nonbank lending relationships attenuate the bank lending channel and support real economic activity.

Next, we turn to nonbank lending to U.S. households and focus first on auto loans, which account for over 30 percent of total consumer credit. For this market, we have detailed, household-level data from Equifax, a major credit bureau. We document that banks retrench in response to a contractionary monetary policy shock. This reduction is not driven by weaker credit demand but by banks' funding conditions as nonbank lenders expand auto

[3]We will provide evidence across different industries and firm types in our loan-level analysis to further test whether results are different in industries and firms more affected by soft information.

credit supply to households. A one standard deviation contractionary monetary policy shock leads to a 10 percent increase in nonbank auto credit. Banks cut auto credit at the same rate. In the aggregate, we do not find any effect of monetary policy on auto credit supply.

Exploiting regional heterogeneity in the auto loan market for identification purposes, we show that households living in counties historically more dependent on nonbank credit experience a larger expansion of nonbank auto credit after a monetary contraction. Nonbank lenders are more likely to expand operations in locations in which they are already present as they have e.g. better information. Conversely, banks may retrench more in counties in which they have a weaker presence. We find that banks reduce credit more in counties in which they historically extended less credit. Nonbanks completely offset this retrenchment. In the aggregate, we do not find any effect of monetary policy on auto credit supply. This finding suggests that nonbank lending by providing a perfect substitute for bank lending limits the response of household consumption to monetary policy and thereby significantly attenuates the bank lending channel of monetary policy.

We then test whether the effects are larger for low credit score borrowers. By interacting historic dependence on nonbank credit with monetary policy and the household risk score, we can also alleviate remaining concerns about time-varying unobservable county-level conditions—that is, we include county-time fixed effects. We confirm perfect substitution between bank and nonbank credit and also find that nonbank credit is more sensitive to monetary policy for low credit score borrowers. This finding suggests that nonbanks take more risk in response to a monetary contraction.

To assess the real effects of substitution in consumer lending, we study whether auto sales are affected by monetary policy. Since most auto sales use some form of financing and our results on auto credit show perfect substitution between bank and nonbank credit, monetary policy is unlikely to affect auto sales. Indeed, we find no significant effect of monetary policy on auto sales on the county level. Only in counties in which substitution of bank and nonbank credit is limited—that is, in counties with a historically low nonbank dependence—do auto sales (and credit) fall in response to a monetary contraction.

Last, we study the largest lending market, mortgages, using HDMA data. We use the confidential version, which unlike the publically available version includes the mortgage origination date allowing us to study mortgage origination on the quarterly level.[4] Controlling for demand at the county-level, we find that nonbanks expand lending relative to banks after a monetary contraction. In response to a one standard deviation contractionary monetary policy shock, the relative expansion of nonbanks is about 10 percent. As in the auto loan market, nonbanks expand mortgage lending more in locations in which they are already present, while banks retrench more in counties in which they have a weaker presence. However, overall substitution is limited in the conforming mortgage market. Differently, we find that substitution is almost perfect in the higher risk jumbo mortgage market.

There are two potential reasons why we observe differences in the substitution from bank to nonbank lenders across mortgage markets. First, the conforming mortgage market is considerably larger and nonbanks may face balance sheet constraints preventing perfect substitution in this market. The second reason is that information about the local housing market is crucial in the mortgage origination process. As such, substitution from bank to nonbank lenders is limited by the extent of historical nonbank presence. Moreover, consistent with the other markets, the expansion of nonbanks is stronger in the riskier segment (the jumbo vs. the conforming segment).

Our results show that the transmission of monetary policy varies across credit markets. Markets in which banks are more special (e.g. syndicated loans) experience only a limited expansion of nonbank credit and therefore less attenuation of the potency of monetary policy. However, across all markets nonbanks significantly increase the risk-taking channel after a

[4]The non-confidential HMDA has data only at the yearly level, which is not ideal to study the effects of high frequency phenomena such as monetary policy.

tightening of monetary policy. One remaining question is why nonbanks are able to expand their credit supply after a monetary contraction. To answer this questions, we investigate the connection between monetary policy and nonbank funding conditions. Using aggregate data for the money market fund (MMF) sector, we show that MMFs experience inflows in response to a contractionary monetary policy shock. Moreover, we show that MMFs increase their holdings of bonds and (asset-backed) commercial paper. In other words, MMFs provide more funding to nonbank lenders after a monetary contraction allowing nonbanks to expand their credit supply.

Our paper contributes to the monetary policy literature. There is a large literature showing that banks cut the supply of credit due to tighter monetary policy conditions: the so-called bank lending channel of monetary policy (e.g., Bernanke and Blinder (1988, 1992), Kashyap and Stein (2000), Jimenez et al. (2012), Drechsler, Savov, and Schnabl (2017)), in turn affecting the credit channel of monetary policy (Bernanke and Gertler 1995). However, as highlighted above, theory is not clear on whether nonbanks can mitigate the credit supply reduction. Therefore, a key contribution of our paper is to show that the presence of nonbanks attenuates the bank lending channel, so that total credit reacts less after a tightening of monetary policy when nonbanks are present. However, this attenuation varies substantially by borrower type: total credit and real effects are largely neutralized in consumer loans and the associated consumption, but not in corporate loans and investment. Moreover, we also contribute to the literature on the risk-taking channel of monetary policy (e.g., Adrian and Shin (2010), Jimenez et al. (2014), and dell'Ariccia, Laeven, and Suarez (2017)) by analyzing this channel for *both* banks and nonbanks. In particular, we find that nonbanks concentrate their lending more on riskier borrowers when monetary policy conditions are tighter, whichin conjunction with the results on relatively higher credit supply from less regulated nonbanks than from bankssuggest a different interpretation on the risk-taking channel of monetary policy from the existing papers on the literature using only bank loans.

One recent paper, Chen, Ren, and Zha (2018), analyzes the impact of monetary policy on banks and shadow banks and concludes that nonbank lenders reduce the effectiveness of monetary policy in China.[5] Our paper differs on multiple dimensions. Our results show that the substitution is larger (and complete) in consumer loans rather than corporate loans and mortgages; however, the risk-taking by nonbanks is similar across all three markets. Differently from the Chinese paper, we use firm-level and household-level loan data to trace the effectiveness of monetary policy, which allows us to test whether or not credit demand factors matter. Chen, Ren, and Zha (2018) use bank-level data and hence cannot identify credit demand versus supply driven effects. We find that in corporate loans, demand effects are crucial for the results. Unlike the Chinese paper, we also analyze the risk-taking channel of monetary policy associated to nonbanks. Moreover, our setting focuses on differences in funding rather than heavy bank regulation in bank quantities (both in lending and liquidity) for Chinese banks when monetary policy changes. In addition, Chinese monetary policy targets M2 (quantities) whereas US monetary policy is primarily based on prices (e.g. short-term rates). Finally, we use monetary policy shocks (based on policy surprises) to better identify the role of monetary policy. Importantly, we also analyze the real effects associated with credit supply and monetary policy.

We also contribute to the literature on nonbanks. The increased presence of nonbanks in lending markets can be attributed to technological advances, liquidity transformation, and superior information (Buchak et al. 2018a; Moreira and Savov 2017; Ordoñez 2018). Bank regulation contributed to more nonbank participation in the syndicated loan market (Irani et al. 2018). This increased presence of nonbanks in many credit markets may lead to better allocation of risk and lower borrowing costs for households (Fuster et al. 2018) and firms

[5]Buchak et al. (2018b) assess the interplay of nonbank lenders and monetary policy in a structural model. Drechsler, Savov, and Schnabl (2019) study the expansion of nonbank lending between 2004 and 2006.

(Ivashina and Sun 2011; Nadauld and Weisbach 2012; Shivdasani and Wang 2011), though it may results in worse real effects and asset-price effects in crisis times (Irani et al. 2018). Relative to this literature, we show that monetary policy affects nonbank presence, and that there is more risk-taking by nonbanks when monetary policy tightens, thereby changing the distribution of risk in the economy.

The paper proceeds as follows. Section 2 summarizes the data that we use in the paper. Section 3 presents the results and the empirical strategy for the response of nonbank credit extended to corporate borrowers to monetary policy shocks, while Section 4 examines household credit. In section 5 we study bank and nonbank lending in the mortgage market. Section 6 provides evidence on the effect of monetary policy on nonbank funding conditions. Section 7 concludes.

2 Data

2.1 Monetary policy measures

Our main measure of monetary policy is the time series of monetary policy shocks constructed by Gertler and Karadi (2015). This measure is based on high-frequency changes in three-month-ahead Fed Funds futures around FOMC policy announcements (referred to as FF4 by Gertler and Karadi (2015)). Following Coibion (2012) and Nelson, Pinter, and Theodoridis (2017), we convert this measure of *shocks* to monetary policy into a *level* measure by taking the cumulative sum. This measure is available from 1990 to 2012.

We use two additional measures of monetary policy in robustness tests: the Fed Funds target rate, and the shadow rate of Wu and Xia (2016). The shadow rate is essentially equal to the effective Fed Funds rate when this is above the zero lower bound. But unlike the Fed Funds rate, the shadow rate is not bounded below by zero. Using these alternative measures of monetary policy also allows us to extend our analysis to 2017. Figure 1 shows the time series of these three monetary policy measures.

2.2 Syndicated loans

Our analysis of the syndicated loan market is based on the DealScan dataset. This provides transaction-level information on syndicated loan originations, including the identities of the borrowers and lenders.

Importantly, DealScan provides a lender classification, which allows us to identify most lenders as either banks or nonbanks. We define the two groups as follows:

- **Banks:** US bank, Western European bank, foreign bank, mortgage bank, Middle Eastern bank, Eastern European/Russian bank, Asia-Pacific bank, thrift / S&L, African bank (plus unclassified firms that have 'bank' in the name).

- **Non-banks:** insurance company, corporation, finance company, investment bank, mutual fund, trust company, leasing company, pension fund, distressed (vulture) fund, prime fund, CDO, hedge fund, other institutional investor.

As shown by Roberts (2015), many observations in DealScan are likely to be amendments to existing loans rather than new originations, and it is often difficult to distinguish between amendments and originations. We drop loans that we identify as likely to be amendments, because these do not necessarily involve 'new' money.[6]

We match the loan-level data in DealScan to borrower-level data in Compustat using the link provided by Chava and Roberts (2008). We collapse the dataset to the borrower-quarter level or the borrower-lender-quarter level. This typically involves summing over multiple loan

[6]Specifically, we drop a loan if it satisfies one of the following three criteria: First, the loan has the word "amends" in the comment. Second, at the time that the new loan is originated, there is already an outstanding loan of the same type to the same borrower with maturity date within one year of the maturity date of the new loan. Third, at the time that the new loan is originated, there is already an outstanding loan of the same type to the same borrower with dollar amount within 25% of the amount of the new loan. This approach identifies around 30% of all term loans and revolvers in DealScan as being potential amendments.

facilities within a loan package (for example, a loan package will often consist of both a term loan and a revolving credit facility). However this aggregation only rarely involves summing over multiple packages, because borrowers rarely take out multiple packages within the same quarter. In some regressions, we also separately consider term loans and revolving credit facilities (these loan types make up around three-quarters of all loan facilities). Summary statistics for the merged DealScan-Compustat dataset are provided in Table 1.

Figure 2 shows the evolution of bank and nonbank syndicated lending in the US.[7] Over the full sample period (1990-2017), nonbank lending has accounted for around 9% of total syndicated lending, by dollar volume. However there has been substantial heterogeneity over time: between 1995 and 2007, nonbank lending increased from less than 5% to more than 20% of the total market.

2.3 Credit Bureau Data

We use data from the Federal Reserve Bank of New York/Equifax Consumer Credit Panel (FRBNY/Equifax CCP). Equifax is one of the three major credit bureaus in the United States. The FRBNY/Equifax CCP provides individuals' outstanding loan balances, broken down by category of loan (auto loan, credit card, mortgage, etc.). For auto loans the data set provides loan balances by lender type (bank and nonbank) but the identities of individual lenders are not provided. These data are available quarterly and extend back to 1999. We draw a 10 percent random sample from Equifax, which yields a panel of about 1.6 million households.

While the credit bureau data include auto loan balances by lender type, they do not provide an indicator variable for new auto loans. For each type of lender, we therefore identify new auto loans by a positive change in the balance of at least $500. We are interested in the net extension of credit. We compute the net new loan amount as the difference between the

[7]This chart only use loans where lender shares are observed.

current quarter auto loan balance and the previous quarter auto loan balance.[8]

The key nonbank lenders in the auto loan market are finance companies. These nonbanks account for about 40 percent of auto loans in the U.S. The extension of auto loans by these nonbanks is not uniform across the country: some counties depend more on nonbank credit than others. Following Benmelech, Meisenzahl, and Ramcharan (2017), we construct a measure of a county's historical dependence on nonbank auto credit using the ratio of county-level auto loan balances outstanding to nonbanks divided by county-level total auto loan balances outstanding at the beginning of the sample (1999Q1).

Table 2 show summary statistic for the Equifax sample on the household and county level. The average nonbank share in 1999Q1 is 0.53 on the county level but there is considerable variation in this measure of dependence on nonbank credit. For instance, the inter-quartile range is 0.37. Figure 3 visualizes the local variation in county-level nonbank dependece. This local variation allows us to isolate the effects of monetary policy.

2.4 Mortgage Data

We use the confidential mortgage application data collected under the Home Mortgage Disclosure Act (HMDA). HMDA records the vast majority of approved home mortgages in the United States. The loan-level data include loan and borrower characteristics as well as the name of the lender. We use the respective GSE-limits to distinguish conforming and jumbo mortgages.[9] Conforming mortgages have loan amount up to the GSE-limit, while jumbo loans exceed the GSE-limit.

Different from the publicly available HMDA data, this dataset includes the origination date for each mortgage. This additional information allow us to ex- amine of bank and

[8]We only observe credit-financed auto purchases in the FRBNY/Equifax CCP data and no cash purchases. Our measure therefore focuses on the intensive margin of financing composition—that is, the substitution between bank and nonbank credit.

[9]We match the specific MSA-level limits to the HDMA data.

nonbank lenders response to monetary policy innovation at the quarterly level. For identification, we exploit both, loan-level and county-level lending patterns.

To identify nonbank lenders in the HDMA data, we follow Buchak et al. (2018a). The algorithm is described in detail in Appendix A. Table 3 shows the summary statistics for the HMDA data.

3 Monetary Policy and Nonbank Lending to Firms

In this section we explore the relationship between monetary policy and nonbank lending to firms using data on syndicated loan originations. We then study how monetary policy affects the distribution of risk between bank and nonbank lenders and the real effects associated with nonbank lending.

We assess whether nonbanks expand credit supply relative to their bank peers in response to a monetary policy shock. Nonbank lenders active in the syndicated loan market such as investment banks rely heavily on short-term funding (e.g. repo) to fund themselves. Hence after a monetary contraction nonbanks should be able to compete more intensive with banks and increase their market share in the syndicated loan market.

We start with a regression analysis of loan amounts extended by nonbanks and banks. We estimate the following equation at the borrower-quarter level without controlling for firm-specific demand:

$$\text{Log(Quantity)}_{b,t} = \beta_1 \text{Monetary Policy}_{t-1} + \beta_2 \text{Macroeconomic Controls}_{t-1} + \alpha + \varepsilon_{b,t} \quad (1)$$

Table 5 shows the results from estimating equation 1. Nonbank lending declines in response to a contractionary monetary policy shock (column 1). However, this reduction in lending is smaller than the reduction by banks (column 2). Consequently, the nonbank share increases after a monetary contraction (column 3). We find similar effects when including industry fixed effects (column 4-6).[10] The fact that both bank and nonbank lending decline after a monetary contraction suggests that demand for credit in the syndicated loan market is sensitive to monetary policy. A second factor possibly limiting substitution between bank and nonbank lenders is that this market relies on soft information and therefore has high switching cost.

Having documented that the market share of nonbanks increases after a monetary contraction, we now tighten identification by exploiting the structure of the syndicated loan market. This structure allows us to identify the effects of monetary policy on nonbank lending for two reasons. First, syndicated loan facilities are extended by multiple lenders to one borrower. This feature allows us to analyze within-borrower variation at the time of loan origination alleviating concerns about unobservable borrower or loan characteristics. Specifically, we use borrower-quarter fixed effects, which are, except for rare cases, equivalent to loan package fixed effects and control for unobserved borrower characteristics at the time of loan origination in the spirit of Khwaja and Mian (2008) and Jimenez et al. (2012).[11] Second, while borrowers choose the lead arranger, the participating members of the syndicate are typically beyond the borrower's control as they are the result of a book building process (Bruche, Malherbe, and Meisenzahl 2017).[12] Hence, the composition of the syndicate originating the loans is typically not affected by the borrower's loan demand but by the overall credit supply provided by different types of financial institution. We exploit the supply-driven composition of syndicates to isolate differential responses of credit supply of different financial institutions to a monetary policy shock.

At the loan level, we first test whether nonbanks expand their syndicated lending relative

[10] In the appendix, table B2, we show that these results are robust to including firm controls and trends as well as weighting observations by loan size and using other measures of monetary policy.

[11] When we split the sample by term loans and revolving credit lines, the borrower-quarter fixed effects are de facto loan facility-fixed effects (Irani and Meisenzahl 2017).

[12] Most lead arrangers are banks.

to banks. We then test our second hypothesis that the effect is stronger for riskier firms. We estimate the following regression.

$$\begin{aligned}\text{Log(Quantity)}_{b,l,t} &= \beta_1 \left(\text{Nonbank}_l \times \text{Monetary Policy}_{t-1}\right) \\ &\quad +\beta_2 \left(\text{Nonbank}_l \times \text{Macroeconomic Controls}_{t-1}\right) + \alpha_{b,t} + \delta_l + \varepsilon_{b,l,t}\end{aligned} \tag{2}$$

wherhe b indexes borrowers, l indexes lenders, and t indexes quarters. The dependent variable, $\text{Log(Quantity)}_{b,l,t}$, is the log of the amount of credit extended by lender l to borrower b in quarter t. In separate regressions, we consider total lending, total term loans, and total revolving credit facilities. Nonbank_l is a dummy variable indicating non-bank lenders. The main explanatory variable of interest is the interaction of the nonbank dummy with $\text{Monetary Policy}_{t-1}$, which is measured as cumulative sums of Gertler-Karadi shocks (demeaned). We also include interactions of the dummy variables with four demeaned macroeconomic controls: VIX, GDP growth, one quarter ahead GDP forecast, and CPI inflation. We saturate the model with borrower-quarter fixed effects to account for unobservable borrower and loan characteristics at the time of origination. We also include lender fixed effect to account for time-invariant lender characteristics (e.g. the business model).

Table 6, panel A shows the results of estimating equation 2 for the sample of dollar-denominated loans extended to U.S. borrowers. Since we include borrower-time fixed effects, we control for credit demand and unobservable firm characteristics at the time of loan origination (Jimenez et al. 2012; Khwaja and Mian 2008). We find that nonbanks expand credit supply to firms in response to a monetary policy shock when compared to their bank peers for the same borrower in the same quarter. This result holds for total lending (column 1), term loans (column 2), and credit line (revolver) extensions (column 3).[13] In other words, the funding mix in corporate lending syndicated shifts from banks to nonbanks after a monetary

[13] We find similar results when we use the monetary policy measure of Wu and Xia (2016) or the Federal Funds Rate.

contraction.

We now assess our second hypothesis that this substitution is stronger for riskier loans. We study which type of borrower is benefitting most from the substitution of bank credit with nonbank credit. For this purpose, we use the DealScan-Compustat merged sample provided by Michael Roberts and use the S&P long-term issuer credit rating as an indicator for borrower risk. Specifically, we interact a high-yield rating indicator with our nonbank and macroeconomic variables.[14] The variable of interest is the triple interaction of the nonbank indicator with the monetary policy variable and the high-yield rating indicator. Given that banks typically retrench from the riskiest borrowers first (de Jonge et al. 2018; Liberti and Sturgess 2018), we expect the substitution to be strongest for the marginal, more risky borrowers—that is, we expect the coefficient on the triple interaction to be positive and significant.

Table 6, panel A, columns 4-6 show the results of including the triple interaction in equation 2. We find that overall subsitution is larger for high-yield borrowers (column 4). This effect is driven by credit lines (column 6): for term loans, we find no association between substitution and borrower risk (column 5).[15]

Table 6, panel B, shows the results of estimating the regressions in panel A without borrower fixed effects. Comparing the results in panel A to those in panel B therefore allows us to assess the impact of firms' credit demand. The magnitude and the significance of the point estimates change significantly. We therefore conclude that accounting for demand factors is crucial for understanding how the bank-nonbank financing mix of corporate loans changes after a monetary contraction.

A natural question is whether the relative expansion of nonbank credit affects firm-level

[14] We also include the lower interactions as controls.

[15] In the appendix, we assess potential international spillovers from U.S. monetary policy to nonbank lending. We consider the sample of loans where the borrower country is not the USA. This approach is similar to Bräuning and Ivashina (2017) who study whether U.S. monetary policy affects the loan supply to international borrowers generally. We find significant spillovers of monetary policy.

outcomes. To answer this question, we test our third hypothesis: that having an existing relationship with nonbank lenders increases credit supply to a borrower after a monetary contraction, and that this expansion of credit supply has real effects on the firm level. A key friction in the syndicated loan market is that lending is based on soft information (Sufi 2007). Hence, borrowers with prior relationships with nonbanks should experience a larger increase in credit supply from nonbanks after a monetary contraction. To measure whether a borrower has prior nonbank relationships, we construct an indicator variable that is equal to one if the firm has borrowed from a nonbank in a previous syndicated loan. We only consider prior loans that were originated at least 2 years before the current quarter.[16] Our hypothesis is that borrowers with prior nonbank relations receive more credit and are therefore able to reduce precautionary cash holdings and increase investment. To test this hypothesis, we estimate the following regression:

$$
\begin{aligned}
\text{Outcome}_{b,t} \quad = \quad & \beta_1 \left(\text{Nonbank Relation}_b \times \text{Monetary Policy}_{t-1}\right) \\
& + \beta_2 \left(\text{Nonbank Relation}_l \times \text{Macroeconomic Controls}_{t-1}\right) + \alpha_b + \delta_{i,t} + \varepsilon_{b,t}
\end{aligned} \tag{3}
$$

where b indexes borrowers, i indexes borrower industry, and t indexes quarters. We consider several different dependent variables: the log of the amount of credit obtained through the syndicated loan market in quarter t, the log of total debt on the balance sh eet, the log of leverage, the log of the ratio of liquid assets to total assets, and the log of the ratio of property, plant and equipment to total assets. As explained above, Nonbank Relation$_b$ is a dummy variable indicating nonbank participation in prior syndicated loans (excluding loans in the last two years). The main explanatory variable of interest is the interaction of the Nonbank Relation dummy with Monetary Policy$_{t-1}$. As before, we also include interactions

[16]We use this time window to avoid potential issues with refinancing. The results do not change if we instead include all previous loans.

of the nonbank relation dummy with four macroeconomic controls. We saturate the model with borrower fixed effects and industry-quarter fixed effects to account for unobservable borrower characteristics and industry-wide shocks.

Table 7 shows the results from estimating equation 3. We find that borrowers with prior nonbank relationships receive more new credit in the syndicated loan market after a monetary contraction (column 1). Firms without prior nonbank relationships are not able to substitute syndicated loans with other types of credit, as firms with prior nonbank relationships also exhibit higher total debt (column 2) and higher leverage (column 3) after a monetary contraction. Having access to additional credit as a result of prior nonbank relationships reduces the need for precautionary savings in the form of liquid assets (column 4). Firms with prior nonbank relationships are also able to invest more in property, plants and equipment (column 5).

In sum, the results presented in this section show that nonbanks expand credit supply in the syndicated loan market relative to banks after a contractionary monetary policy shock. This suggests that the presence of nonbank lenders can significantly attenuate the bank lending channel of monetary policy. Moreover, the substitution from bank credit to nonbank credit is strongest for riskier borrowers, suggesting that nonbank lenders also attenuate the risk-taking channel of monetary policy. The partial substitution of bank credit with nonbank credit has real effects as firms with prior nonbank relationships receive more credit and invest more following a monetary contraction.

4 Monetary Policy and Nonbank Lending to Households

In this section we explore the relationship between monetary policy and nonbank lending to consumers using credit bureau data on auto loans.

The present auto credit market is large because most new cars in the United States are bought on credit or leasing. At its peak in 2006, auto credit was \$785 billion, accounting for 32% of consumer debt. Nonbank lenders have always been an important source of financing for auto purchases and particularly so for borrowers with lower credit scores (Barron, Chong, and Staten 2008). Most nonbank lenders in the auto loan market use short-term funding markets to finance the extension of new loans. These loans are then securitized. Benmelech, Meisenzahl, and Ramcharan (2017) provide a detailed account of the evolution of nonbank credit in the auto loan market and its financing.

A key difference between auto lending and syndicated lending (studied in the section above) is that the auto loan application process is standardized. Auto lenders rely on hard information such as the credit score and income when deciding whether to extend a loan, whereas lenders in the syndicated loan market also use soft information in their lending decisions. By studying the response of auto lending by banks and nonbanks to a monetary contraction, we gain insights into whether substitution between bank and nonbank credit is stronger when only hard information is used in lending decisions.

To test the main hypothesis that nonbank lenders increase credit supply while banks decrease credit supply in response to a contractionary monetary policy shock, we estimate the following regression:

$$\text{Log(Auto Credit)}_{j,t} = \beta_1 \text{MP}_{t-1} + \beta_2 \text{Macroeconomic Controls}_{t-1} + \beta_3 X_{j,t-1} + \alpha_j + \varepsilon_{j,t} \quad (4)$$

where $\textit{Auto Credit}_{jt}$ the log of new auto loan amounts in county j in quarter t . MP_{t-1} is the stance of monetary policy in $t-1$ measured by the Gertler-Karadi cumulative shock time series.[17] Macroeconomic Controls_{t-1} is a vector of macroeconomic controls that includes GDP, GDP forecast, inflation and the VIX. $X_{j,t-1}$ is a vector of time-varying county-level

[17]We obtain similar results when we use the Wu-Xia shadow rate.

controls (the average credit-bureau reported risk score and income). We saturate the model with county-fixed effects (α_j) to account for differences in time-invariant county-level characteristics.

Following Drechsler, Savov, and Schnabl (2017), we expect banks experiencing deposit outflows after a monetary contraction to cut auto lending—that is, we expect β_1 to be negative and significant for *new auto loans extended by banks.* To be clear, a negative coefficient could also be interpreted as a drop in credit demand. One indication that the reduction in bank lending is attributable to tighter bank funding constraints rather than a drop in demand would be an increase in lending by nonbanks —that is, we expect β_1 to be positive and significant for *new auto loans extended by nonbanks.*

Table 8 shows the results of estimating equation 4. Consistent with relative relaxation of nonbanks' funding constraints after a monetary contraction, we find that nonbanks increase auto lending (column 1). Banks reduce auto lending in response to a monetary contraction (column 2). A 25 bps surprise increase in the policy rate leads to reduction in new auto loans extended by banks by over 5 percent. The increased nonbank lending activitysuggests that the fall in bank lending is driven by credit supply rather than credit demand. In the aggregate, we find that the substitution between bank and nonbank lending is perfect. The estimated effect of changes in monetary policy on total auto credit in a county is close to zero and statistically insignificant (column 3).

To better understand the substitution between bank and nonbank auto credit, we now study whether substitution occurs uniformly or whether lenders make strategic choices regarding expansion and retrenchment. We consider two potential determinants of expansion and retrenchment. The first is whether a county is considered a core market as lenders cut credit in non-core markets (de Jonge et al. 2018; Liberti and Sturgess 2018). Benmelech, Meisenzahl, and Ramcharan (2017) argue that for historical reasons nonbank auto lenders have a large presence in some counties and a weak presence in other counties. We measure historical dependence as the share of auto loan balances outstanding extended by nonbanks at the beginning of the sample (1999Q1). In line with the bank lending channel, we hypothesize that banks retrench more from markets in which they have a weaker presence. Second, in line with the risk-taking channel, we hypothesize that banks retrench more from lending to more risky borrowers (de Jonge et al. 2018; Liberti and Sturgess 2018). Figure 3 shows that there is significant variation in the historical dependence on nonbank credit across U.S. counties.

To test these hypotheses, we estimate the following model:

$$\text{Log(Auto Credit)}_{j,t} = \beta_1 \text{Nonbank Share 1999}Q1_j \times MP_{t-1} + \gamma X_{it-1} + \alpha_j + \theta_t + \epsilon_{jt} \quad (5)$$

where $\text{Log(Auto Credit)}_{j,t}$ is the log of new auto loan amounts in county j in quarter t . *Nonbank Share 1999Q1*$_j$ is county's j dependency on nonbank credit measured as the share of auto loan balances outstanding extended by nonbanks as of 1999Q1. MP_{t-1} is the stance of monetary policy in $t-1$ measured by the Gertler-Karadi cumulative shock time series.[18] X_{jt-1} is a vector of controls that includes the interaction of dependency with GDP, inflation and the VIX. We control for local economic conditions by including average risk score and county-level income. We saturate the model with county-fixed effects (α_j) to account for differences in time-invariant county-level characteristics and with time fixed effect (θ_t).

Table 9 shows the results of estimating equation 5 at the county level. Columns 1 and 2 show that nonbanks expand auto credit more in response to higher monetary policy rates in counties historically more dependent on nonbank credit, while banks' auto credit contracts more in these counties. Given an average *Nonbank Share 1999Q1*$_j$ of 0.53, the coefficients are comparable in magnitude to the ones reported in table 8. The point estimates in columns 1 and 2 suggest that, on the county-level and controlling for aggregate demand, there is also

[18]We obtain similar results when we use the Wu-Xia shadow rate.

close-to-perfect substitution between bank and nonbank credit.[19] Indeed, column 3 shows no significant net effect of contraction monetary policy on auto credit at the county level.[20] These results are consistent with banks retrenching to focus on their core markets.

We now examine whether banks retrench more from markets with more risky borrowers on average (as measured by risk scores). Table 9, columns 4-6 show the results for counties with below median average credit score and columns 7-9 show the results for counties with above median average credit score. We find that in both samples nonbank lenders expand after a contractionary monetary policy shock while banks retrench. The overall effect, shown in column 6 and 9, shows that the substitution between bank and nonbank lenders is perfect a t the county level in both samples.[21]

Two concerns remain. First, using data on the county-level potentially mask important heterogeneity among borrowers within a county. Second, while we control for county-level income and county-fixed effects, time-varying demand factor could still affect our results.

To address both concerns, we use household-level data. We identify whether a household took out a new auto loan, the loan amount, and the lender type (bank, nonbank). The data also include balances on other loans (mortgage, credit card, consumer loans), the individuals age, and a bankruptcy indicator, which allows us to better control for potential demand and risk factors.

We first replicate the county-level findings using the household-level data by estimating

[19]In theory, these results could be consistent with and expansion of bank credit and contraction of nonbank credit (but these effects weaker in counties with higher nonbank share). However, the aggregate results in table 8 and Ludvigson (1998) show that this is not the case.

[20]We find similar patterns when we use the number of loans instead of the loan amount, see Table B3 in the appendix.

[21]The increase in nonbank lending results in considerable increased in the new lending market share of nonbanks. In the appendix, table B5 shows that the new lending market share of nonbank increases by about 7 percent in response to a 100 basis points increase in the policy rate. Ludvigson (1998) documents an increase in the market share of nonbanks in the auto loan market after a monetary contraction for the period 1965-1994 using aggregate time series. In table B4 we confirm that the effect is not concentrated in the low credit score counties.

the following model:

$$\text{Auto Loan}_{ijt} = \beta_1 \text{Nonbank Share } 1999Q1_j \times MP_{t-1} + \gamma X_{ijt-1} + \alpha_j + \theta_t + \epsilon_{ijt} \tag{6}$$

where *Auto Loan*$_{ijt}$ is either an indicator equal to 1 if for household i in county j a new auto loan appears in quarter t or the log of new auto loan amount. *Nonbank Share 1999Q1*$_j$ is county's j dependency on nonbank credit measured as the share of auto loan balances outstanding extended by nonbanks. MP_{t-1} is the stance of monetary policy in $t-1$ measured by the Gertler-Karadi cumulative shock time series.[22] X_{ijt-1} is a vector of controls that includes the interaction of dependency with GDP, inflation and the VIX as well as the household's birth year (fixed effects), outstanding credit card balance, outstanding mortgage balance, outstanding other consumer loan balance, and risk score. We control for local economic conditions by including county-level income. We saturate the model with county-fixed effects (α_j) to account for differences in time-invariant county-level characteristics and with time fixed effect (θ_t).

Again, the key variable is the interaction of the historical dependence of a county on non-bank credit interacted with the monetary policy variable $\text{Nonbank Share}1999Q1_j \times MP_{t-1}$. We expect the coefficient β_1 to be positive for auto loans *financed with nonbank credit.* The expansion of nonbank credit should substitute for bank credit. As on the county-level, the extent of substitutions is given by estimating β_1 with any auto loan as dependent variable.

Table 10 shows the results of estimating equation 6. Nonbank increase lending (column 1) while banks cut lending (column 2). For this measure of new credit, the expansion of nonbank credit also nearly exactly offsets the reduction in credit supply by banks (column 6). This perfect substitution between bank and nonbank credit suggests that the deposit outflows experienced by banks are matched by an expansion of funding available to nonbanks

[22]We obtain similar results when we use the Wu-Xia shadow rate.

in the money markets. Nonbanks take advantage of this funding expansion by increasing credit supply to households.

Turning to the prosensity of getting a new auto loan, we find that households is more likely to receive an auto loan from a nonbanks after a contractionary monetary policy shock (column 4) than from a bank (column 5).[23] This point estimate implies that for a household living in a county with average historical dependence (0.57), a household's probability of obtaining an auto loan from a nonbank increases by 0.05 percentage points in response to a 25 basis points increase in the policy rate. This represents a 5 percent increase in the probability to obtain an auto loan from a nonbank in a given quarter (mean 1 percent). Column 5 shows that this expansion of nonbank auto credit is matched by a similar decrease in the extension of auto credit by banks. On net, we find no effect for the propensity to obtain an auto loan from any source (column 6). In sum, the household-level data confirm the county-level findings: following a monetary contraction substitution between bank and nonbank lenders is perfect in the auto loan market.

A remaining concern with this specification is that we cannot control for time-varying county characteristics other than income as most consistent annual county-level data are only available from 2004 on. We address this concern by using county-time fixed effects below.

A natural question is which types of borrowers are mostly likely to be affected by changes in the credit supply from banks and nonbanks. Previous research, e.g. Liberti and Sturgess (2018) and de Jonge et al. (2018) suggests that banks are more likely to reduce the extension of credit to the least credit worthy borrowers.[24]

[23]Benmelech, Meisenzahl, and Ramcharan (2017) show that auto sales dropped more in counties more dependent on nonbank auto credit during the 2007-08 financial crisis. Our results hold when we constrain the sample to the pre-crisis period.

[24]In the appendix, we show that counties with a concentrated banking sector, measured as concentration in deposit taking, exhibit an increase in auto credit provided by banks (Table B7). This finding is consistent with banks focusing on their core markets or markets in which they have price setting power. However, we find that the include bank deposit taking concentration does not affect our main result.

To test whether the substitution is dependent on borrower risk, we include a triple interaction of borrower's lagged credit score, the county's Nonbank Share1999Q1, and monetary policy as well as the triple interaction of borrower's lagged credit score and the county's Nonbank Share1999Q1 with of with all other macroeconomic variables.[25] We hypothesis that banks retrench more from borrowers with lower credit scores while nonbanks expand in this segment. In other words, the higher the borrower's credit score, the less likely is a reduction of credit supply from banks and an increase of credit supply from nonbanks. Hence, we expect the coefficient on the triple to be negative and significant for the loan amount financed by nonbanks and positive for the loan amount financed by banks. This specification allows us to include county-time fixed effects to alleviate concerns that our results are driven by local demand varying systematically with the historical dependence on nonbank auto credit over the cycle.

Table 11 shows the results of estimating the effect of monetary policy on auto loans by borrower risk. Column 1 shows that nonbank increase their credit supply to lower credit score borrowers in response to higher monetary policy rates. This expansion of nonbank credit occurs when banks retreat from this segment of the market and shift credit supply to relatively better borrowers (column 2). The substitution between banks and nonbank is perfect across the credit risk spectrum (column 3). We obtain similar results when we use the log new loan amount as dependent variable (columns 4-6).[26]

To better understand whether the substitution between bank and nonbank auto credit has real effects, we study county-level auto sales using data from Polk. We replicate the

[25]We also include the interaction of the macroeconomic variables with the risk score. The interaction of the Nonbank Share1999Q1 is absorbed by the county-quarter fixed effects.

[26]Unfortunately, we do not observe the interest rates charged on an auto loan. However, the literature suggests that this substitution means that, while low credit score borrowers may still have access to auto loans, the terms of these loans are likely to be less favorable. Specifically, Charles, Hurst, and Stephens (2008) show that auto loan interest rate vary by source of financing and that nonbanks tend to charge higher rates.

county-level findings using the auto sales data by estimating the following model:

$$Log(\text{Auto Sales}_{jt}) = \beta_1 \text{Nonbank Share 1999}Q1_j \times MP_{t-1} + \gamma X_{jt-1} + \alpha_j + \theta_t + \epsilon_{jt} \quad (7)$$

where *Auto Sales*$_{jt}$ is the logarithm of total new auto sales inn quarter t in county j.

Table 12 shows the results from estimating equation 7. We find no effect of monetary policy on auto sales when we use the Gertler-Karadi cumulative shock time series as our measure of monetary policy (column 1). When we use Wu-Xia shadow rate (column 2) or the federal funds rate (column 3) we find a small, but statistically positive effect of monetary policy on auto sales. However, this effect is not robust to weighting the observation with past county-level income (columns 4-6).

We then test whether montary policy has real effects in terms of auto sales in counties in which the substitution between bank and nonbank credit is limited. Since nonbanks tend to expand credit in counties in which they had a historically large market share, we use an indicator variable that is equal to 1 if a county's historical dependence on nonbank credit is in the lowest 25th percentile. In these counties substitutions is expected to be limited and hence auto sales should fall in response to a retrenchment of bank credit. Columns 7-9 show that this is the case. We find a negative and statistically significant effect of monetary policy on auto sales in low nonbank dependency counties regardless of the monetary policy measure used.[27]

Taken together, the results presented in this section show that contractionary monetary policy shocks shift the auto credit supply from banks to nonbanks. Where substitution between bank and nonbank credit is limited, we find real effects of monetary policy. More generally, our results indicate that in lending markets in which lending decisions are based on hard information substitution between bank and nonbank lender can be perfect.

[27]These results are robust to weighting the observations with past county-level income.

5 Monetary Policy and Mortgage Lending

In this section we explore the relationship between monetary policy and nonbank mortgage lending using the confidential HMDA data, which include the mortgage issuance date allowing us to construct quarterly panel data.

With about $10 trillion outstanding balances, mortgages to households are the largest lending market in the United States. Mortgages are originated by bank and nonbank lenders. These lenders choose to either hold the mortgages on their balance sheets, securitize them, or to sell them in the secondary market. The main buyers of mortgages are government-sponsored enterprises (GSEs); Fannie Mae and Freddie Mac and, before the 2008 financial crisis, private-level securitizers.

In general, two types of mortgages exit: conforming mortgages—mortgages that are not insured or guaranteed by the federal government and adhere to the guidelines set by the GSEs—and jumbo mortgages—mortgages that exceed the guidelines set by the GSEs and are therefore not eligible to be purchased, guaranteed or securitized by the GSEs. As the conforming mortgage market and the jumbo mortgage market differ regarding the lender's post-origination options, we consider mortgage originations in these markets separately.

Lenders originate mortgages using their own funds, even if they sell the loan later. To finance the origination of new loans, nonbank lender use warehouse financing—-short-term credit extended to the nonbank lender until the mortgage is sold into the secondary market. Some buyers in the secondary market, especially issuers of asset-backed securities (ABS) that engaged in private-label securitization, rely themselves heavily on short-term funding. ABS accounted for $350 billion of mortgages in 2000, $2.2 trillion in 2007, and $1 trillion in 2012, highlighting the importance short-term funding market conditions for mortgage originations.

For lenders, knowledge of the local housing market, such as recent trends in neighborhoods and range of possible assessments for the house value, is crucial for the lending process.

Otherwise, the application process for mortgages is standardized. Mortgage lenders rely on hard information such as the credit score and income when deciding whether to extend a loan, and this information also determines the lender's ability to sell the mortgage to the GSEs.

To test the main hypothesis that nonbank lenders increase credit supply while banks decrease credit supply in response to a contractionary monetary policy shock, we use county-level data from HMDA on newly extended mortgages by mortgage and lender type. To reduce noise in the share of nonbank participation potentially introduced by smaller counties, we restrict our sample to counties with at least 10 mortgage originations in each quarter. This restriction reduces the sample to 860 counties covering about 90 percent of all mortgages reported in HMDA (see Figure A1). We estimate the following regression:

$$\begin{aligned} \text{Log(Mortgage Amount)}_{j,t} = & \alpha_j + \beta_1 \text{MP}_{t-1} + \beta_2 \text{Macroeconomic Controls}_{t-1} + \\ & \beta_3 X_{j,t-1} + \varepsilon_{j,t} \end{aligned} \tag{8}$$

where *Mortgage Amount*$_{jt}$ is the log of new mortgage loan amounts in county j in quarter t . MP_{t-1} is the stance of monetary policy in $t-1$ measured by the Gertler-Karadi cumulative shock time series.[28] Macroeconomic Controls_{t-1} is a vector of macroeconomic controls that includes GDP, GDP forecast, inflation and the VIX. $X_{j,t-1}$ includes time-varying county-level controls (log income). We saturate the model with county-fixed effects (α_j) to account for differences in time-invariant county-level characteristics.

Table 13 shows the results of estimating equation 8. We start by analyzing the response of conforming mortgage originations, shown in columns 1-4. In response to a contractionary monetary policy shock, originations of conforming mortgages by banks fall (column 1). Similarly, originations of conforming mortgages by nonbanks fall (column 2), leading to an

[28]We obtain similar results when we use the Wu-Xia shadow rate.

overall reduction in the origination of conforming mortgages (column 3) and a somewhat lower nonbank market share (column 4).

In the jumbo loan market, we find a small positive effect of monetary policy on bank originations of jumbo mortgages (column 5). The effect is larger for nonbanks (column 6). The estimated effect on total jumbo loan originations shown in column 7, is positive and significant with the nonbank market share increasing slightly , though this increase is not statistically significant (column 8).

A significant shortcoming of the aggregate approach is that nonbanks were differentially affected by demand factors and especially the financial crisis of 2007-09 in the second half of your sample, potentially explaining the reduction in nonbank market share in the conforming loan market. We tackle this identification issue below by using first time fixed effects and then county-time fixed effects.

We now tighten identification by exploiting geographical variation of nonbank presence in the mortgage market. As information about the local market is a crucial input in lending decisions, the ease of substitution between bank and nonbank lenders may depend on the historic presence of nonbanks in a county. We expect that substitution is more likely to take place when nonbank lenders have accumulated information about the local market by having extended loans in a county in the past. We therefore construct the county-level historic dependence of nonbank market credit as the share of mortgage originated by nonbank lenders in the first quarter of 1990Q1 similar to the construction of nonbank share in the auto loan market in the section above. This approach allows us to include time fixed effects, alleviating concerns that our results are driven by the effects of the financial crisis of 2007-09.

Figure 4 shows the distribution of county-level nonbank dependence in the mortgage market as of 1990Q1. We hypothesize that banks reduce mortgage lending more in counties with a large nonbank presence in response to a monetary contraction while nonbanks expand. We expect this to hold both for loans that are held on the balance sheet and loans that are sold as nonbanks finance both type of loans with short-term credit while banks lose deposits.

To test these hypotheses, we estimate the following model:

$$\begin{aligned} \text{Log(Mortgage Amount)}_{j,t} = & \beta_1 \text{Nonbank Share } 1990Q1_j \times MP_{t-1} + \\ & \gamma X_{j,t-1} + \alpha_j + \theta_t + \epsilon_{j,t} \end{aligned} \tag{9}$$

where $\text{Log(Mortgage)}_{j,t}$ is the log of new mortgage amounts in county j in quarter t . *Nonbank Share 1990Q1*$_j$ is county's j dependency on nonbank credit measured as the share of mortgages extended by nonbanks in 1990Q1. MP_{t-1} is the stance of monetary policy in $t-1$ measured by the Gertler-Karadi cumulative shock time series.[29] X_{jt-1} is a vector of controls that includes the interaction of dependency with GDP, inflation and the VIX. We control for local economic conditions by including average risk score and county-level income.[30] We saturate the model with county-fixed effects (α_j) to account for differences in time-invariant county-level characteristics and with time fixed effects (θ_t).

Table 14 shows the results of estimating equation 9 for conforming and jumbo mortgage origination. As hypothesized, banks reduce conforming mortgage lending in response to a contractionary monetary policy shock (column 1), while nonbanks expand (column 2). On net, we find a statistically significant, negative effect on total conforming mortgage originations (column 3). The market share of nonbank lender significantly increases after a contractionary monetary policy shock (column 4). Economically, in a county with an average Nonbank Share 1990Q1, these point estimates translate into a reduction in bank lending by 3 percent and into an increase in nonbank lending by 6.5 percent in response to a one standard deviation increase in the monetary policy variable.[31]

In the jumbo mortgage market, we find similar lending patterns. Banks retrench after

[29] We obtain similar results when we use the Wu-Xia shadow rate.

[30] Consistent time series for local house prices going back to 1990 are not available.

[31] We find the same pattern when we use the log number of loans originated as dependent variable.

a contractionary monetary policy shock (column 5), while nonbanks expand (column 6). However, controlling for aggregate demand, in this market we find no effect of monetary policy on total jumbo mortgage origination (column 7) at the county level. Consistent with the banks' retrenchment and the nonbanks' expansion, the nonbank market share increases (column 8).[32]

In sum, the results suggest substitution from banks to nonbanks in the conforming and the jumbo mortgage markets. Substitution in the conforming mortgage market is limited, while substitution in the jumbo market appears to be perfect. One potential explanation for this difference is that the conforming mortgage market is considerably larger and nonbanks face balance sheet constraints, limiting their ability to substitute for the retrenchment of banks.

A remaining concern is that our results are driven by county-specific time trends that correlate with the dependence on nonbank credit. For instance, since consistent house price time series on the local level since 1990 are not available, local housing market developments could drive our results. To alleviate these concerns about time-varying, local economic conditions, we now investigate the mortgage lending behavior in response to monetary policy at the loan level. By doing using, we exploit variation between bank and nonbank lenders in response to monetary policy shock within a county-quarter. We estimate the following regression:

$$\begin{aligned}\text{Log(Mortgage Amount)}_{i.k,j,t} =& \beta_1 \text{Nonbank Dummy}_{k,t} \times MP_{t-1} + \\ & \beta_2 \text{Nonbank Dummy}_{i,k,j,t} + \gamma X_{t-1} + \alpha_{j,t} + \theta_k + \epsilon_{i,k,j,t}\end{aligned} \tag{10}$$

where $\text{Log(Mortgage)}_{i,j,t}$ is the log of new mortgage amount of loan i in county j in quarter t. *Nonbank Dummy*$_{i,t}$ is equal to 1 if the lender in loan i was a nonbank in quarter t.[33] MP_{t-1}

[32]These results are not driven by the financial crisis, see Table B8.

[33]Some lenders in the mortgage market switch charters over our sample period. The point estimate β_2 is

is the stance of monetary policy in $t-1$ measured by the Gertler-Karadi cumulative shock time series.[34] X_{jt-1} is a vector of controls that includes the interaction of $Nonbank\ Dummy_{i,t}$ with GDP, inflation and the VIX. We saturate the model with lender fixed effects (θ_k) and with county-time fixed effects (α_{jt}) to account for differences in time-varying county-level characteristics such as economic conditions and house prices.

Table 15 shows the results of estimating equation 10. On the loan-level nonbank lender extend more credit after a monetary contraction in the market for conforming loans (column 1). The economic magnitude of the estimated coefficient is sizable. A one standard deviation increase in the monetary policy variable increases nonbank lending on the loan level by 1.4 percent. In the riskier jumbo mortgage market, we find that nonbanks also expand originations in both markets (column 2) and this expansion is larger than in the conforming mortgage market. This last finding is consistent with nonbank attenuating the risk-taking channel of monetary policy.

Taken together, the evidence in this section shows that there is substitution between bank and nonbank mortgage lenders after a contractionary monetary policy shock. This substitution is somewhat limited in the conforming mortgages market and appears to be perfect in the jumbo mortgage market. As a result of this substitution effects, the presence of nonbanks attenuates the effectiveness of the bank lending channel of monetary policy in the mortgage market.

6 Monetary Policy and Nonbank Funding

So far, we have documented that nonbanks lend more when monetary policy tightens. We now examine one mechanism that enables nonbanks to expand lending after a monetary contraction.

identified by these switchers. For details on the classification, see Appendix.

[34] We obtain similar results when we use the Wu-Xia shadow rate.

Stein (2013) claims that an advantage of monetary policy is that it "gets in all the cracks" of the financial system and therefore affects all financial intermediaries in a similar manner. At the same time, Drechsler, Savov, and Schnabl (2017) show that banks experience deposit outflows in a monetary tightening cycle, which in turn reduces banks' ability to lend. This observation raises two interrelated questions about other parts of the financial system: 1) To which financial products do the deposits flow? and 2) Do financial products that experiences inflows provide funding for nonbanks?

With respect to the first question, we observe that one alternative to bank deposits is money market funds (MMFs). The returns of these funds tend to track the federal funds rate closely. If banks do not raise their deposit rates to match increases in the federal fund rate (as shown by Drechsler, Savov, and Schnabl (2017)) then depositors will find switching from holding deposits to holding money market fund shares attractive (Xiao 2017). To test whether this occurs, we estimate how MMF assets respond to monetary policy. Using data from the Financial Accounts of the United States, we estimate the following equation:

$$\begin{aligned} \text{MMF Asset Growth}_t \;=\; & \beta_1 \text{Monetary Policy}_{t-1} + \\ & \beta_2 \text{Macroeconomic Controls}_{t-1} + \text{Trend}_t + \text{Trend}_t^2 + \alpha + \epsilon_t \end{aligned} \tag{11}$$

A monetary contraction should lead to bank deposit outflows and, as a result, money market funds should experience inflows. Hence, we expect the coefficient on Monetary Policy$_{t-1}$, β_1, to be positive and significant.

Table 4 shows the results of estimating equation 11. We measure monetary policy using the cumulative sums of Gertler-Karadi shocks. Money market funds grow more during a monetary contraction (column 1). This relationship holds when excluding the 2007/08 financial crisis (column 2). This finding shows that after a monetarty contraction deposits migrate from the banking sector to money market funds.

In response to the second question, whether financial products that experiences inflows provide funding for nonbanks, we note that, among other short-term investments, money markets funds invest in short-term paper of firms and asset-backed commercial paper (ABCP). Many nonbanks rely on this type of funding from money market funds.[35] Table 4, columns 3 and 4 show that money market funds also buy relatively more open market paper and corporate bonds during a monetary contraction. This suggests that more funding becomes available to nonbank lenders.[36] This finding is consistent with Xiao (2017) who, using disaggregated MMF data, shows that MMFs increase their holdings of commercial paper and ABCP when the federal funds rate is higher.

In sum, funding available to nonbank lenders increase after a monetary tightening allowing them to increase lending as documented above.

7 Conclusion

The significantly larger presence of nonbank lenders in many credit markets critically affects the effectiveness of monetary policy. Deposits leaving the banking sector after a monetary contraction flow to the shadow banking system that provides financing to nonbank lenders. Nonbank lenders are therefore able to increase lending after a monetary contraction, offsetting the reduction in lending by banks and reducing the effectiveness of monetary policy.

This attenuation of the bank lending channel is particular pronounced in the consumer credit market that relies on hard information. Nonbank lenders expand credit provision in the auto loan market by about 10 percent after a one standard deviation increase in the policy rate. This increase matches the retrenchment by banks. On net, we do find a statistically significant effect of monetary policy on total auto credit. We also find evidence for substitu-

[35]For instance, Benmelech, Meisenzahl, and Ramcharan (2017) document that auto finance companies funded the vast major for their credit supply with ABCP. For a more general overview of funding flows, see Pozsar et al. (2013).

[36]We find similar results when we take the monetary policy measure byWu and Xia (2016).

tion in the mortgage market and in the syndicated corporate loan market. Nonbanks expand lending relative to their bank peers after a monetary contraction. On aggregate, syndicated corporate lending and total mortgage falls due to reduced demand but credit provision shifts to nonbank funding.

The changes in the mix of credit providers after a monetary contraction that we document also raises questions about the interplay of monetary policy, the structure of credit markets, and financial stability. If nonbank providers become more important sources of credit for the real economy in the wake of a monetary contraction then risk in the financial system becomes more diversified. At the same time, a large presence of nonbank credit providers is likely to limit central banks' ability to counteract subsequent credit market disruptions. More research is needed to understand these linkages.

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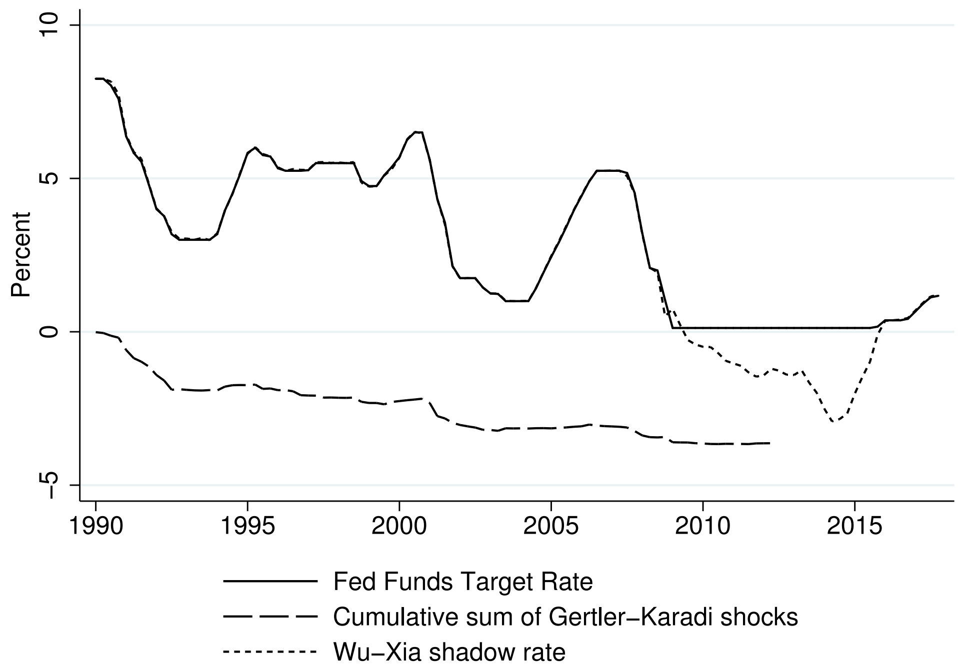
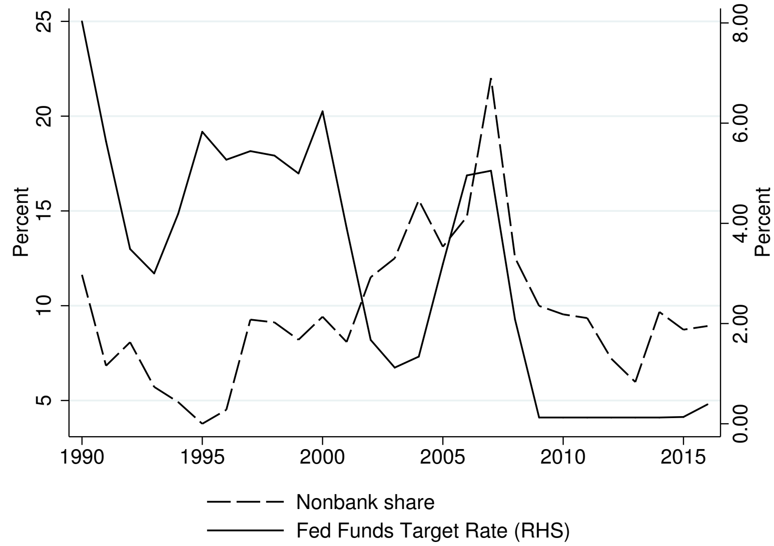
Figure 1: Monetary policy measures



Notes: The chart shows the Federal Funds Target Rate, shadow rates of Wu and Xia (2016), and cumulative sums of the monetary policy shocks of Gertler and Karadi (2015). Quarterly averages.

Figure 2: Syndicated lending in the US: Nonbank lending as proportion of total



Notes: The chart shows annual syndicated lending quantities from DealScan, and annual averages of the Federal Funds Target Rate. The figure shows nonbank lending as a proportion of total lending. The sample consists of dollar-denominated loans to borrowers headquarted in the US. Only loans where lender shares are observed in DealScan are included.

Figure 3: Distribution of Household Dependence on Nonbank Auto Credit

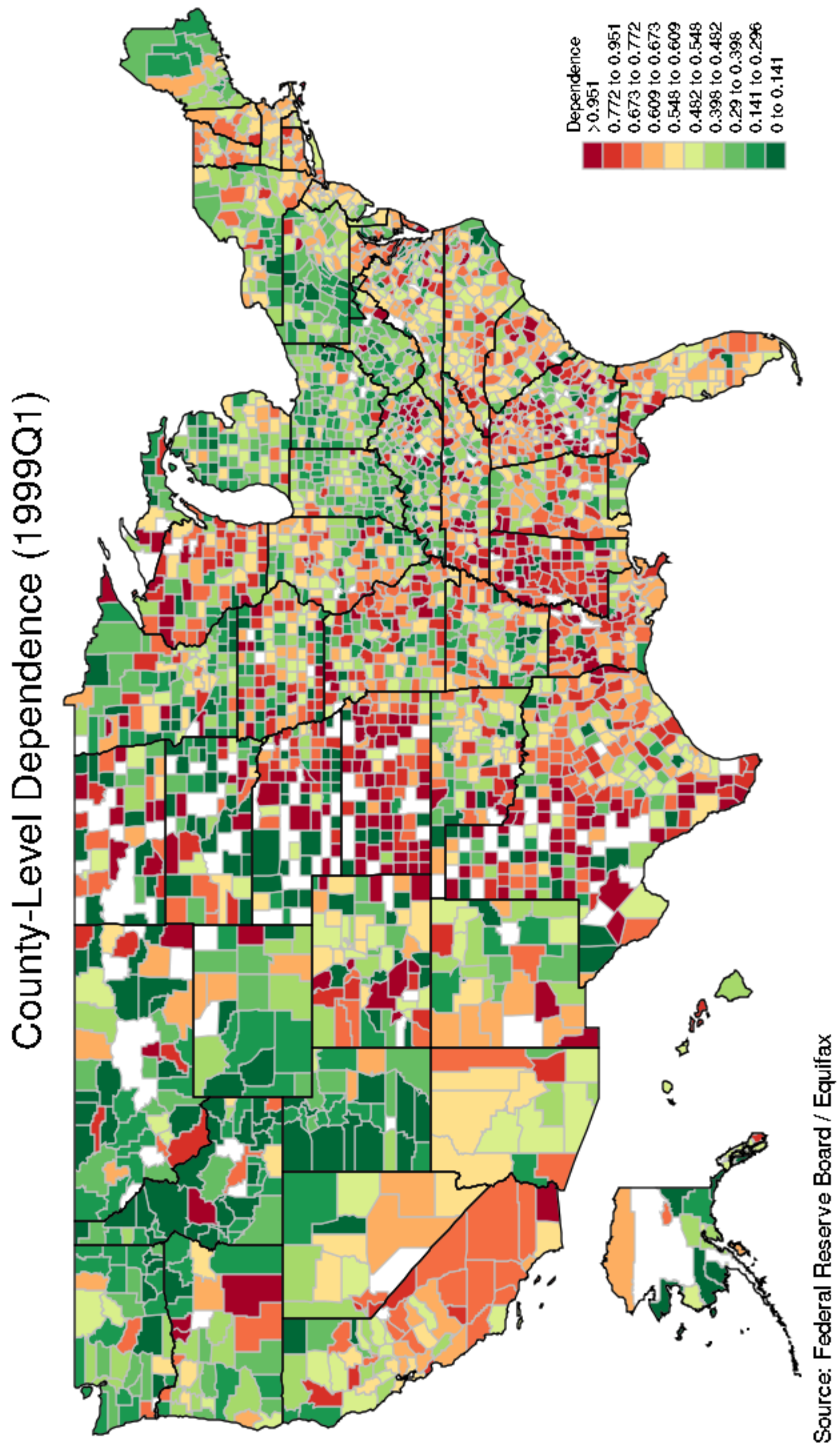


Figure 4: Distribution of Household Dependence on Nonbank Mortgage Credit

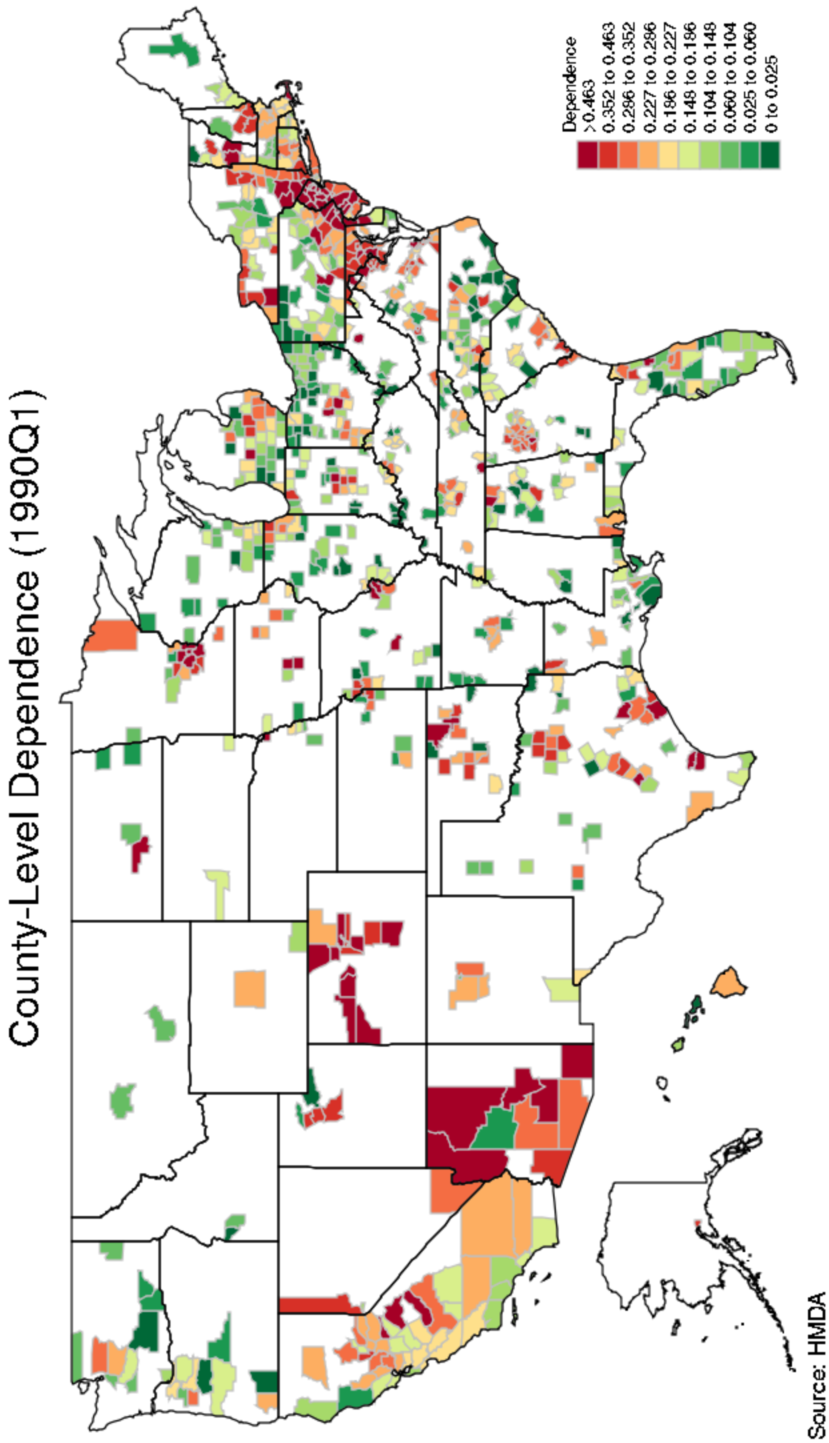


Table 1
Summary Statistics: DealScan and Compustat

This table shows summary statistics for the merged DealScan-Compustat dataset. The sample consists of dollar-denominated loans to borrowers headquartered in the US. The sample period is 1990-2012. All variables are defined in Appendix A. The variables 'log total borrowing' and 'nonbank relation' are defined using all loans, even where lender shares are unobserved. The other variables derived from DealScan are defined using only loans where lender shares are observed.

Variable	N	mean	sd	p25	p50	p75
		Borrower-quarter level				
Log total borrowing	62,558	18.28	1.554	17.40	18.32	19.27
Log nonbank amount	5,471	17.26	1.355	16.45	17.22	18.10
Log bank amount	15,545	17.84	1.878	16.52	17.91	19.16
Log nonbank share	5,471	-1.311	1.165	-2.244	-1.312	0
Nonbank relation	623,359	0.226	0.418	0	0	0
Log total debt	371,420	5.061	2.684	3.240	5.138	6.801
Log leverage	371,305	-1.406	1.026	-1.798	-1.199	-0.802
Log liquid asset ratio	546,829	-3.118	1.681	-4.152	-2.974	-1.868
Log PPE / assets	519,073	-1.760	1.306	-2.433	-1.495	-0.749
Log total assets	578,098	6.166	2.598	4.375	6.059	7.764
High yield	194,721	0.427	0.495	0	0	1
		Borrower-lender-quarter level				
Nonbank lender	103,337	0.109	0.312	0	0	0
Log all loans amount	103,337	16.98	1.100	16.38	17.03	17.63
Log term loan amount	18,763	16.25	1.222	15.49	16.22	16.99
Log revolver amount	60,303	16.85	1.003	16.30	16.91	17.49

Table 2
Summary Statistics Equifax

This table shows the summary statistics for the Equifax sample. All variables are defined in Appendix A.

Variable	N	mean	sd	p25	p50	p75
			Individual Level			
Nonbank Share 1999	54,258,810	0.57	0.16	0.49	0.59	0.67
New Loan Finance	54,258,810	0.01	0.10	0	0	0
New Loan Bank	54,258,810	0.01	0.09	0	0	0
Log Finance Amount	54,258,810	0.09	0.95	0	0	0
Log Bank Amount	54,258,810	0.08	0.89	0	0	0
Bankruptcy	54,258,810	0.00	0.05	0	0	0
Log Credit Card Balance	54,258,810	1.40	2.96	0	0	0
Log Consumer Credit Balance	54,258,810	0.33	1.55	0	0	0
Log Mortgage Balance	54,258,810	2.65	4.90	0	0	0
HHI	54,258,810	0.17	0.11	0.11	0.15	0.21
Riskscore	54,258,810	687	107	608	708	780
Log Income	54,258,810	21.05	1.92	19.68	21.28	22.49
			County-Level			
Nonbank Share 1999	2,936	0.53	0.28	0.35	0.55	0.72
Market Share (Amt)	157,981	0.35	0.37	0	0.33	0.63
Market Share (Loans)	157,981	0.36	0.38	0	0.27	0.67
Log New Loans Finance	157,981	0.80	0.90	0	0.69	1.10
Log New Loans Bank	157,981	0.80	0.88	0	0.69	1.39
Log Finance Amount	157,981	6.14	5.26	0	9.29	10.69
Log Bank Amount	157,981	5.95	5.34	0	9.25	10.68
HHI	157,981	0.32	0.21	0.18	0.26	0.39
Mean Riskscore	157,981	687.17	32.80	666.02	689.53	709.72
Log Income	157,981	18.12	1.72	16.95	17.97	19.11

Table 3
HMDA Summary Statistics

Variable	N	mean	sd	p25	p50	p75
			County-Level			
Log Bank Conforming Amount	76,451	10.02	1.46	9.04	10.02	10.99
Log Nonbank Conforming Amount	76,451	9.55	1.93	8.46	9.65	10.82
Log Total Conforming Amount	76,451	10.58	1.51	9.53	10.57	11.62
Nonbank Market Share Conforming Loans	76,451	0.41	0.15	0.31	0.42	0.51
Log Bank Jumbo Amount	76,451	6.86	3.72	5.99	7.70	9.31
Log Nonbank Jumbo Amount	76,451	4.62	4.22	0	6.06	8.10
Log Total Jumbo Amount	76,451	7.22	3.71	6.22	7.96	9.63
Nonbank Market Share Jumbo Loans	76,451	0.19	0.23	0	0.11	0.33
1990q1 Reliance on Nonbanks Banks	76,451	0.20	0.17	0.07	0.17	0.30
Log of Lagged Income	76,451	19.78	1.38	18.77	19.66	20.65
			Loan-Level - Conforming Loans			
Logged Loan Value	58,799,736	4.65	0.76	4.25	4.77	5.174
Female Dummy	58,799,736	0.27	0.44	0	0	1
African American Dummy	58,799,736	0.06	0.25	0	0	0
Logged Applicant Income	58,799,736	4.161	0.63	3.76	4.14	4.53
Nonbank Dummy	58,799,736	0.45	0.50	0	0	1
			Loan-Level - Jumbo Loans			
Logged Loan Value	5,329,921	6.02	0.441	5.7	5.97	6.26
Female Dummy	5,329,921	0.17	0.37	0	0	0
African American Dummy	5,329,921	0.04	0.19	0	0	0
Logged Applicant Income	5,329,921	5.11	0.64	4.70	5.01	5.42
Nonbank Dummy	5,329,921	0.35	0.48	0	0	1

Table 4
Monetary Policy and MMF Flows

The table shows the results of estimating equation 11. Asset Growth is the quarterly growth rate of total MMF sector assets. CP/Bond growth is the quarterly growth rate of holdings of open market paper and corporate bonds. All variables are defined in Appendix A. The sample period is 1990-2012.

	Asset Growth		CP/Bond Growth	
	All	Pre-2008	All	Pre-2008
	(1)	(2)	(3)	(4)
GK Lagged	0.0826***	0.105***	0.103***	0.103***
	(0.0249)	(0.0204)	(0.0296)	(0.0240)
GDP Lagged	0.000538	0.000941	0.00377	0.00434
	(0.00170)	(0.00221)	(0.00273)	(0.00331)
GDP Forecast Lagged	0.000882	0.00422	-0.00207	-0.00571
	(0.00728)	(0.00757)	(0.00997)	(0.00923)
VIX Lagged	-0.000280	-0.000832	-0.000973	-0.00254
	(0.000868)	(0.00114)	(0.00112)	(0.00167)
Inflation lagged	0.00597	-0.0143	-0.00580	-0.00876
	(0.00615)	(0.00856)	(0.0102)	(0.0107)
Trends	YES	YES	YES	YES
Observations	86	67	86	67
R^2	0.332	0.297	0.347	0.299

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5
Aggregate Syndicated Loans: Substitution across Banks and Nonbanks

The table shows estimated regression coefficients for equation 1. The dependent variable is the log of lending quantity from DealScan (columns 1, 2, 4, 5) or the log share of nonbanks in syndicates (columns 3, 6). Only observations where lender shares are observed are included. GK refers to lagged cumulative sums of the monetary policy shocks of Gertler and Karadi (2015) for the US. The regressions are at quarterly frequency. The sample period is 1990-2012. The sample consists of dollar-denominated loans where the borrower country is the USA. Standard errors clustered by borrower and quarter. All variables are defined in Appendix A.

	Nonbank Amount (1)	Bank Amount (2)	Nonbank Share (3)	Nonbank Amount (4)	Bank Amount (5)	Nonbank Share (6)
GK	-0.522***	-0.885***	0.633***	-0.503***	-0.807***	0.562***
	(0.0407)	(0.0410)	(0.0280)	(0.0392)	(0.0367)	(0.0272)
VIX	0.0124	0.0340***	-0.0203***	0.00953	0.0260***	-0.0173***
	(0.00792)	(0.0101)	(0.00635)	(0.00705)	(0.00806)	(0.00569)
Inflation	0.202***	0.195***	-0.105***	0.190***	0.173***	-0.0734***
	(0.0373)	(0.0443)	(0.0300)	(0.0317)	(0.0357)	(0.0270)
GDP growth	-0.00848	-0.0198	0.00736	-0.00807	-0.00884	0.00190
	(0.0162)	(0.0256)	(0.0169)	(0.0132)	(0.0214)	(0.0151)
GDP growth forecast	0.0765	0.223***	-0.0494	0.0509	0.131**	-0.0138
	(0.0543)	(0.0728)	(0.0482)	(0.0467)	(0.0579)	(0.0469)
Industry FEs	No	No	No	Yes	Yes	Yes
Observations	5,349	15,195	5,349	5,041	14,598	5,041
Number of borrowers	3,876	9,508	3,876	3,572	8,923	3,572
Number of quarters	90	90	90	90	90	90
R-squared	0.0942	0.154	0.216	0.278	0.364	0.369

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6
Impact of US monetary policy on US corporate lending

The table shows estimated regression coefficients for equation 2 including interactions with a high-yield borrower indicator. The dependent variable is the log of lending quantity from DealScan. Only observations where lender shares are observed are included. GK refers to lagged cumulative sums of the monetary policy shocks of Gertler and Karadi (2015) for the US. The regressions are at quarterly frequency. The sample period is 1990-2012. Macroeconomic controls are inflation, GDP growth, GDP growth forecast and VIX. Macroeconomic controls are lagged by one quarter. The sample consists of dollar-denominated loans where the borrower country is the USA. Standard errors clustered by borrower, lender and quarter. All variables are defined in Appendix A.

	Log(Total Credit Amount)					
	All Loans	Term Loans	Revolvers	All Loans	Term Loans	Revolvers
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Borrower-quarter fixed effects						
Nonbank x GK	0.135***	0.193***	0.0585**	0.0549	0.308**	-0.0135
	(0.0309)	(0.0488)	(0.0268)	(0.0387)	(0.128)	(0.0512)
Nonbank x High yield x GK				0.205***	-0.0261	0.194***
				(0.0456)	(0.103)	(0.0520)
Nonbank x High yield				0.0748*	0.190**	0.0255
				(0.0395)	(0.0861)	(0.0506)
Double Interactions	Yes	Yes	Yes	Yes	Yes	Yes
Triple Interactions	No	No	No	Yes	Yes	Yes
Borrower-quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Lender FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92,971	14,956	54,312	46,900	4,887	25,107
Number of borrowers	6,589	1,921	4,804	1,744	393	1,336
Number of lenders	2,053	1,026	1,268	1,186	520	845
Number of quarters	90	90	90	90	88	90
R-squared	0.811	0.817	0.829	0.792	0.819	0.804
Panel B: No borrower fixed effects						
Nonbank x GK	0.105**	0.0839	-0.0116	0.147*	0.428**	-0.00855
	(0.0408)	(0.0916)	(0.0514)	(0.0883)	(0.165)	(0.0567)
Nonbank x High yield x GK				0.109	-0.236	0.135*
				(0.0718)	(0.148)	(0.0785)
Nonbank x High yield				-0.468***	-0.445***	-0.363***
				(0.0699)	(0.133)	(0.0622)
Double Interactions	Yes	Yes	Yes	Yes	Yes	Yes
Triple Interactions	No	No	No	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Lender FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	98,851	16,736	58,124	47,280	4,996	25,294
Number of borrowers	10,140	3,405	7,530	1,902	487	1,451
Number of lenders	2,270	1,161	1,414	1,204	527	855
Number of quarters	90	90	90	90	88	90
R-squared	0.335	0.393	0.289	0.291	0.536	0.314

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7
Real effects of US monetary policy in the U.S. corporate sector

This table shows estimated regression coefficients for equation 3. The dependent variable in column 1 is the log of total quantity of dollar-denominated syndicated loans, from DealScan. The dependent variables in columns 2 5 are balance sheet variables derived from Compustat (all in logs). GK refers to lagged cumulative sums of the monetary policy shocks of Gertler and Karadi (2015) for the US. 'Nonbank relation is an indicator variable equal to one for firms that have previously borrowed from a nonbank (excluding loans within the previous two years). The regressions are at quarterly frequency. The sample period is 1990-2012. The sample consists borrowers headquartered in the USA. Standard errors clustered by borrower and quarter. All variables are defined in Appendix A.

	(1)	(2)	(3)	(4)	(5)
	Borrowing	Total debt	Leverage	Liquid asset ratio	PPE / Assets
Nonbank relation x GK	0.156***	0.0420**	0.0371**	-0.0654**	0.0326**
	(0.0384)	(0.0182)	(0.0180)	(0.0240)	(0.0137)
Nonbank relation x VIX	0.000944	0.000953	0.00172*	0.00196	-0.000793
	(0.00413)	(0.00114)	(0.00102)	(0.00129)	(0.000598)
Nonbank relation x Inflation	0.0178	-0.00752	-0.0124*	0.00429	-0.000985
	(0.0325)	(0.00567)	(0.00652)	(0.00783)	(0.00304)
Nonbank relation x GDP	0.00616	0.000285	0.000477	-0.00248	-0.000204
	(0.00885)	(0.00202)	(0.00184)	(0.00269)	(0.00113)
Nonbank relation x GDP forecast	-0.0193	0.00947	0.0212***	-0.000485	-0.000983
	(0.0317)	(0.00695)	(0.00730)	(0.00957)	(0.00389)
Log(Borrower assets)	0.373***	0.841***	0.0218*	-0.208***	0.0333***
	(0.0212)	(0.0149)	(0.0110)	(0.00914)	(0.00777)
Borrower FEs	Yes	Yes	Yes	Yes	Yes
Industry-quarter FEs	Yes	Yes	Yes	Yes	Yes
Observations	23,027	340,613	340,560	502,396	476,752
Number of borrowers	5,776	9,748	9,747	10,633	10,225
Number of quarters	90	90	90	90	90
R-squared	0.844	0.925	0.549	0.630	0.872

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8
Aggregate Auto Loans: Substitution across Banks and Nonbanks

This table shows the regression results of equation 4. The dependent variable is the log amount of new auto credit extended by finance companies (column 1), by banks (column 2) and by both sources (3). The sample period is from 1999 to 2012. Standard errors clustered by county and state x quarter. All variables are defined in Appendix A.

	Log New Loan Amount		
	Nonbank	Bank	Total
	(1)	(2)	(3)
Lagged GK	0.207***	-0.269***	-0.00996
	(0.0474)	(0.0467)	(0.0420)
Lagged GDP Forecast	0.0755***	0.165***	0.113***
	(0.0285)	(0.0221)	(0.0228)
Lagged Inflation	0.0323**	-0.0237	0.00153
	(0.0157)	(0.0149)	(0.0142)
Lagged VIX	-0.0132***	-0.00930***	-0.0120***
	(0.00340)	(0.00278)	(0.00266)
Lagged GDP	0.0449***	-0.0570***	-0.00358
	(0.00806)	(0.00745)	(0.00658)
Time-varying County Controls	YES	YES	YES
County FE	YES	YES	YES
Observations	169,216	169,216	169,216
R^2	0.499	0.509	0.530

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9
County-Level Effects on Auto Loans

This table shows the regression results of equation 6. The dependent variable is the log amount of new auto loans extended by finance companies (columns 1, 4, 7), the log amount of new auto loans extended by banks (columns 2, 5, 8), or the log amount of all new auto loans (columns 3, 6, 9). Columns 4-6 show results for counties with an average credit score below the median across all counties. Columns 7-9 show results for counties with an average credit score above the median across all counties. The sample period is from 1999 to 2012. Standard errors are clustered by quarter and county. All variables are defined in Appendix A.

	Log New Credit Amount								
	All Counties			Below Median Risk Score Counties			Above Median Risk Score Counties		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Nonbank	Bank	Total	Nonbank	Bank	Total	Nonbank	Bank	Total
GK x Nonbank Share 1999	0.503***	-0.587***	0.109	0.415***	-0.671***	-0.0268	0.559***	-0.736***	0.114
	(0.0986)	(0.119)	(0.107)	(0.129)	(0.189)	(0.145)	(0.154)	(0.146)	(0.164)
GDP x Nonbank Share 1999	0.0186	-0.0127	0.0257	0.0153	-0.0123	0.0236	0.0249	-0.0148	0.0259
	(0.0182)	(0.0219)	(0.0178)	(0.0217)	(0.0288)	(0.0252)	(0.0284)	(0.0245)	(0.0257)
Inflation x Nonbank Share 1999	-0.0258	0.0572**	0.0182	-0.0383	0.0603	0.0325	-0.0219	0.0113	-0.0311
	(0.0343)	(0.0244)	(0.0318)	(0.0388)	(0.0397)	(0.0537)	(0.0550)	(0.0421)	(0.0383)
VIX x Nonbank Share 1999	0.0215***	-0.0197*	0.00125	0.0322***	-0.0274**	-0.00509	0.00776	-0.0134	0.00392
	(0.00588)	(0.0106)	(0.00891)	(0.00716)	(0.0132)	(0.00933)	(0.0118)	(0.0137)	(0.0141)
GDP Forecast x Nonbank Share 1999	0.0804	-0.0879	-0.0108	0.118*	-0.118	-0.0571	0.0275	-0.0531	0.0275
	(0.0484)	(0.0702)	(0.0557)	(0.0606)	(0.100)	(0.0682)	(0.0764)	(0.0796)	(0.0779)
Time-varying County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	158,461	158,461	158,461	72,059	72,059	72,059	86,270	86,270	86,270
R^2	0.489	0.490	0.502	0.535	0.529	0.547	0.456	0.463	0.472

Standard errors are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10
Household-Level Effects on Auto Loans

This table shows the regression results of equation 6 on the individual level. The dependent variable in column 1 is the log of new auto loan amount extended by finance companies, in column 2 the log of new auto loan amount extended by banks, and in column 3 the log loan amount extended by both sources of financing. The dependent variable is a dummy variable equal to 1 if new auto loans extended by finance companies (column 4), banks (column 5) or both sources of financing (column 6). Standard errors are clustered by quarter and county. The sample period is from 1999 to 2012. All variables are defined in Appendix A.

	Log Amount			New Loan		
	Nonbank	Bank	Total	Nonbank	Bank	Any
	(1)	(2)	(3)	(4)	(5)	(6)
GK x Nonbank Share 1999	0.0312***	-0.0318***	-0.000376	0.00339***	-0.00377***	-0.000542
	(0.00715)	(0.00664)	(0.00113)	(0.000771)	(0.000733)	(0.0104)
GDP x Nonbank Share 1999	0.00121	-0.000614	0.0000482	0.000119	-0.0000705	0.000595
	(0.00109)	(0.00157)	(0.000169)	(0.000115)	(0.000174)	(0.00153)
Inflation x Nonbank Share 1999	-0.000705	0.00301	0.000241	-0.0000785	0.000327	0.00225
	(0.000868)	(0.00297)	(0.000311)	(0.0000944)	(0.000323)	(0.00283)
VIX x Nonbank Share 1999	0.00122***	-0.000230	0.000104	0.000130***	-0.0000250	0.000990
	(0.000394)	(0.000640)	(0.0000708)	(0.0000427)	(0.0000705)	(0.000650)
GDP Forecast x Nonbank Share 1999	0.00404	-0.00312	0.000115	0.000422	-0.000311	0.000956
	(0.00361)	(0.00412)	(0.000536)	(0.000384)	(0.000451)	(0.00498)
Lagged Risk Score	-0.000200***	0.000155***	-0.00000742***	-0.0000228***	0.0000154***	-0.0000446**
	(0.0000142)	(0.00000947)	(0.00000173)	(0.00000149)	(0.000000982)	(0.0000168)
Lagged Mortgage Balance	0.00590***	0.00757***	0.00138***	0.000606***	0.000792***	0.0133***
	(0.000317)	(0.000267)	(0.0000494)	(0.0000330)	(0.0000281)	(0.000474)
Lagged Consumer Loan Balance	0.0154***	0.00955***	0.00262***	0.00164***	0.00101***	0.0247***
	(0.00112)	(0.000375)	(0.000123)	(0.000122)	(0.0000392)	(0.00114)
Lagged Credit Card Balance	0.00441***	0.00769***	0.00125***	0.000450***	0.000813***	0.0120***
	(0.000385)	(0.000307)	(0.0000587)	(0.0000404)	(0.0000324)	(0.000560)
Lagged Bankruptcy Indicator	0.0621***	-0.00341	0.00650***	0.00686***	-0.000355	0.0587***
	(0.00614)	(0.00299)	(0.000751)	(0.000663)	(0.000336)	(0.00698)
County-Level Income	0.000413	-0.00355***	-0.000369**	0.0000349	-0.000405***	-0.00314*
	(0.00128)	(0.000698)	(0.000177)	(0.000133)	(0.0000733)	(0.00170)
County FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Birth Year FE	YES	YES	YES	YES	YES	YES
Observations	54,243,317	54,243,317	54,243,317	54,243,317	54,243,317	54,243,317
R^2	0.005	0.007	0.010	0.005	0.007	0.010

Standard errors are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11
Household-Level Effects on Auto Loans: Risk

This table shows the regression results of equation 6 on the individual level. The dependent variable in column 1 is the log of new auto loan amount extended by finance companies, in column 2 the log of new auto loan amount extended by banks, and in column 3 the log loan amount extended by both sources of financing. The dependent variable is the a dummy variable equal to 1 if new auto loans extended by finance companies (column 4), banks (column 5) or both (column 6). The sample period is from 1999 to 2012. Standard errors are clustered by quarter and county. All variables are defined in Appendix A.

	Log Amount			New Loan		
	Nonbank	Bank	Total	Nonbank	Bank	Any
	(1)	(2)	(3)	(4)	(5)	(6)
GK x Nonbank Share 1999 x Score	-0.0913***	0.147***	0.0521	-0.00972***	0.0162***	0.00601
	(0.0000307)	(0.0229)	(0.0387)	(0.00335)	(0.00250)	(0.00416)
VIX x Nonbank Share 1999 x Score	-0.00217	-0.00327**	-0.000551**	-0.000226	-0.000332**	-0.000566**
	(0.00000149)	(0.00132)	(0.00224)	(00000161)	(0.000140)	(0.000233)
Inflation x Nonbank Share 1999 x Score	0.00647*	0.00776	0.0141	0.000797**	0.00881	0.000167
	(0.00000326)	(0.00949)	(0.0101)	(0.000331)	(0.000964)	(0.00103)
GDP x Nonbank Share 1999 x Score	0.00558*	0.00393	0.00938*	0.000602*	0.0000439	0.00103*
	(0.00311)	(0.00366)	(0.00512)	(0.000355)	(0.000379)	(0.000543)
GDP Forecast x Nonbank Share 1999 x Score	-0.0153	-0.0288***	-0.0440**	-0.00170	-0.00312***	-0.00482**
	(0.0119)	(0.00993)	(0.0183)	(0.00126)	(0.00107)	(0.00192)
Lower-Level Interactions	YES	YES	YES	YES	YES	YES
Individual Characteristics	YES	YES	YES	YES	YES	YES
County-Time FE	YES	YES	YES	YES	YES	YES
Birth Year FE	YES	YES	YES	YES	YES	YES
Observations	54,243,555	54,243,555	54,243,555	54,243,555	54,243,555	54,243,555
R^2	0.009	0.012	0.014	0.009	0.012	0.014

Standard errors are in parentheses. Coefficient multiplied with 1000.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12
Auto Sales and Monetary Policy

This table shows the regression results for the real effects of monetary policy on auto sales. The dependent variable is the log of auto sales. Low Nonbank Share 1999 is a dummy equal to 1 if a county's dependency on nonbank was in the lowest quartile in 1999. Columns 4-6 are weighted with past county-level income. The sample period is from 2002 to 2012. Standard errors are clustered by quarter and county. All variables are defined in Appendix A.

	Log Auto Sales								
	All Counties - Unweighted			All Counties - Weighted			Lowest 25th Nonbank Dependence		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Nonbank Share 1999 x GK	0.0344			0.157					
	(0.0230)			(0.138)					
Nonbank Share 1999 x WX		0.00415*			0.0142				
		(0.00223)			(0.0122)				
Nonbank Share 1999 x FFR			0.00529**			0.0165			
			(0.00261)			(0.0141)			
Low Nonbank Share 1999 x GK							-0.0352**		
							(0.0146)		
Low Nonbank Share 1999 x WX								-0.00396**	
								(0.00148)	
Low Nonbank Share 1999 x FFR									-0.00450**
									(0.00185)
Nonbank Share 1999 x GDP	0.00255*	0.00302**	0.00314**	0.0138**	0.0130**	0.0129**			
	(0.00130)	(0.00117)	(0.00119)	(0.00535)	(0.00597)	(0.00623)			
Nonbank Share 1999 x GDP Forecast	0.000666	0.00439	0.00454	-0.0174	-0.00307	-0.00226			
	(0.00306)	(0.00400)	(0.00423)	(0.0170)	(0.0290)	(0.0299)			
Nonbank Share 1999 x Inflation	0.00340	0.00217	0.00162	0.00664	0.00125	-0.0000632			
	(0.00222)	(0.00208)	(0.00200)	(0.0108)	(0.00977)	(0.0101)			
Nonbank Share 1999 x VIX	-0.000341	0.000127	0.000219	0.000605	0.00133	0.00147			
	(0.000456)	(0.000450)	(0.000447)	(0.00238)	(0.00314)	(0.00314)			
Low Nonbank Share 1999 x GDP							-0.000687	-0.00123	-0.00119
							(0.000814)	(0.000767)	(0.000854)
Low Nonbank Share 1999 x GDP Forecast							-0.00105	-0.00560**	-0.00590**
							(0.00207)	(0.00264)	(0.00291)
Low Nonbank Share 1999 x Inflation							-0.000247	0.000720	0.00106
							(0.00117)	(0.00110)	(0.00113)
Low Nonbank Share 1999 x VIX							0.000384	-0.000215	-0.000256
							(0.000273)	(0.000299)	(0.000324)
County-Level Income	0.407***	0.418***	0.418***	0.518***	0.518***	0.519***	0.395***	0.407***	0.407***
	(0.0276)	(0.0288)	(0.0288)	(0.0561)	(0.0575)	(0.0578)	(0.0272)	(0.0287)	(0.0287)
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	122,991	125,920	125,920	122,991	125,920	125,920	131,468	134,598	134,598
R^2	0.989	0.988	0.988	0.991	0.991	0.991	0.988	0.988	0.988

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13
Conforming and Jumbo Loan Issuance by Lender-Loan Type

Date Range: 1990q2 - 2012q3. All counties issued at least 10 loans in every quarter prior to 2008. Conforming loans are defined as loans beneath the conforming loan limit. Jumbo loans are defined as loans above the conforming loan limit. GK, the MP Shock, is the cumulative sum of monetary policy shocks of Gertler and Karadi (2015). Macro variables are lagged GDP, lagged GDP forecast, lagged inflation, and lagged VIX. All lagged variables are on a one quarter lag. Observations weighted with lagged county-level income. Standard errors are clustered on the county-level.

	Conforming				Jumbo			
	Banks	Nonbanks	Total	Nonbank Share	Banks	Nonbanks	Total	Nonbank Share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GK	-0.109***	-0.459***	-0.165***	-0.0397***	0.109**	0.252***	0.0934**	0.00348
	(0.0168)	(0.0217)	(0.0147)	(0.0023)	(0.0463)	(0.0403)	(0.0427)	(0.00281)
GDP Growth	0.00685***	0.0440***	0.0178***	0.0075***	0.0505***	0.117***	0.0590***	0.00759***
	(0.000990)	(0.00108)	(0.000730)	(0.000160)	(0.00404)	(0.00404)	(0.00398)	(0.000155)
GDP Forecast	0.116***	0.209***	0.148***	0.0184***	0.294***	0.621***	0.324***	0.0256***
	(0.00312)	(0.00390)	(0.00290)	(0.00058)	(0.0139)	(0.0171)	(0.0137)	(0.00057)
Inflation	-0.0535***	-0.265***	-0.112***	-0.0341***	-0.187***	-0.485***	-0.244***	-0.00344***
	(0.00415)	(0.00636)	(0.00347)	(0.00088)	(0.0143)	(0.0166)	(0.0137)	(0.00188)
VIX	-0.00559***	-0.0141***	-0.00789***	-0.0011***	-0.00329*	-0.00425**	-0.00530***	-0.0003*
	(0.000522)	(0.000589)	(0.000412)	(0.000096)	(0.00179)	(0.00188)	(0.00169)	(0.00016)
Log of Lagged Income	1.279***	0.939***	1.161***	-0.0414***	2.442***	1.112***	2.116***	-0.0092***
	(0.0539)	(0.0604)	(0.0467)	(0.0077)	(0.142)	(0.125)	(0.131)	(0.0084)
County FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	76,451	76,451	76,451	76,451	76,451	76,451	76,451	76,451
Adjusted R^2	0.839	0.770	0.864	0.452	0.672	0.622	0.683	0.265
Quarters	89	89	89	89	89	89	89	89
Counties	860	860	860	860	860	860	860	860

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 14
County-Level Dependence: Conforming and Jumbo Loan Issuance

Date Range: 1990q2 - 2012q3. All counties issued at least 10 loans in every quarter prior to 2008. Conforming loans are defined as loans beneath the conforming loan limit. Jumbo loans are defined as loans above the conforming loan limit. GK, the MP Shock, is the cumulative sum of monetary policy shocks of Gertler and Karadi (2015). Macro variables are lagged GDP, lagged GDP forecast, lagged inflation, and lagged VIX. All lagged variables are on a one quarter lag. Observations weighted with lagged county-level income. Standard errors are clustered by county and quarter.

	Conforming				Jumbo			
	Banks	Nonbanks	Total	Nonbank Share	Banks	Nonbanks	Total	Nonbank Share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1990 Nonbank Share x GK	-0.471***	0.796***	-0.136***	0.146***	-0.517***	0.418**	-0.137	0.143***
	(0.0902)	(0.134)	(0.0503)	(0.0167)	(0.155)	(0.191)	(0.144)	(0.0144)
1990 Nonbank Share x GDP Growth	0.0134	-0.0207	0.00471	-0.00254	0.0228	0.00471	-0.0114	0.0033
	(0.0174)	(0.0422)	(0.00662)	(0.00577)	(0.0318)	(0.0672)	(0.0268)	(0.00461)
1990 Nonbank Share x GDP Forecast	0.0653	-0.0217	0.0685***	-0.00930	0.0401	0.660**	0.132	0.0458***
	(0.0450)	(0.110)	(0.0211)	(0.0159)	(0.113)	(0.255)	(0.107)	(0.0166)
1990 Nonbank Share x Inflation	-0.0102	0.443***	0.00853	0.0263*	0.193***	0.162	0.176**	-0.0260**
	(0.0303)	(0.127)	(0.0171)	(0.0139)	(0.0730)	(0.175)	(0.0687)	(0.0130)
1990 Nonbank Share x VIX	0.00992	0.0354**	0.00844***	0.00131	0.0193	0.000457	0.0117	-0.0016
	(0.00644)	(0.0166)	(0.00303)	(0.00224)	(0.0150)	(0.0286)	(0.0143)	(0.00219)
Log of Lagged Income	0.854***	0.623***	0.808***	-0.0316**	1.798***	0.922***	1.555***	-0.0483**
	(0.0654)	(0.0766)	(0.0579)	(0.0131)	(0.187)	(0.293)	(0.182)	(0.0190)
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
County FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	76,451	76,451	76,451	76,451	76,451	76,451	76,451	76,451
Adjusted R^2	0.910	0.898	0.950	0.693	0.713	0.725	0.731	0.350
Quarters	89	89	89	89	89	89	89	89
Counties	860	860	860	860	860	860	860	860

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 15
Loan-Level Regressions on Loan Amounts, by Loan Type

Date Range: 1990q2 - 2012q3. All counties issued at least 10 loans in every quarter of date range. Conforming loans are defined as loans beneath the conforming loan limit. Jumbo loans are defined as loans above the conforming loan limit. The dependent variable is measured in thousands and then logged. MP shock is the cumulative sum of Monetary Policy Shocks from Gertler and Karadi (2015). All macro variables are on a one quarter lag. All macro variables are logged. Applicant controls are race, gender, and income. Standard errors are clustered at the Lender-County level

	Conforming (1)	Jumbo (2)
MP Shock x Nonbank Dummy	0.00672**	0.0254***
	(0.00333)	(0.00195)
GDP Growth x Nonbank Dummy	-0.00422***	0.000128
	(0.000968)	(0.000349)
GDP Forecast x Nonbank Dummy	-0.00989***	-0.000947
	(0.00330)	(0.00135)
Inflation x Nonbank Dummy	0.00790***	0.00205
	(0.00296)	(0.00154)
VIX x Nonbank Dummy	-0.000376	0.000219
	(0.000481)	(0.000162)
Female Dummy	-0.0362***	-0.0178***
	(0.000512)	(0.000459)
African American Dummy	-0.0796***	-0.00918***
	(0.00143)	(0.000741)
Logged Applicant Income	0.382***	0.316***
	(0.00168)	(0.00179)
Nonbank Dummy	0.0263***	-0.0386***
	(0.00678)	(0.00223)
County-Time FE	yes	yes
Lender FE	yes	yes
Observations	58,799,726	5,320,887
Adjusted R^2	0.39	0.66

Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix A

Variable definitions

This appendix presents the definitions for the variables used throughout the paper.

Variable	Definition	Source
Panel A: Macro Variables		
GK	Cumulative Gertler-Karadi Monetary Policy Rate	Gertler and Karadi (2015)
Inflation	Inflation Rate	Federal Reserve Bank of St. Louis
GDP	Gross Domestic Product Growth Rate	Federal Reserve Bank of St. Louis
GDP Forecast	One-quarter-ahead forecast of Gross Domestic Product Growth	Federal Reserve Bank of Philadelphia
VIX	Volatility Index	CBOE
WX	Wu-Xia Shadow Rate	Wu and Xia (2016)
Fed Funds	Federal Funds Target Rate	Federal Reserve Bank of St. Louis
Panel B: Consumer Loans		
Nonbank Share 1999	The share of auto loan balances outstanding extended by nonbank	FRBNY/Equifax CCP
Low Nonbank Share 1999	Indicator equal to 1 if a county's dependency on nonbank was in the lowest quartile	FRBNY/Equifax CCP
HHI	Sum of squared deposit market shares (Drechsler, Savov, and Schnabl 2017)	FDIC
New Loan Nonbank	Indicator equal to 1 if a household received a new auto loan from a nonbank	FRBNY/Equifax CCP
New Loan Bank	Indicator equal to 1 if a household received a new auto loan from a bank	FRBNY/Equifax CCP
Log Amount Nonbank	Log of new auto loan amount extended by a nonbank	FRBNY/Equifax CCP
Log Amount Bank	Log of new auto loan amount extended by a bank	
Market Share	The nonbank share of new auto loan balances outstanding	FRBNY/Equifax CCP
Credit Card Balance	Log of credit card debt outstanding	FRBNY/Equifax CCP
Mortgage Balance	Log of first mortgage debt outstanding	FRBNY/Equifax CCP
Consumer Balance	Log of consumer credit (other than auto loans) outstanding	FRBNY/Equifax CCP
Bankruptcy	Indicator equal to 1 if household had declared either Chapter 7 or 13 bankruptcy	FRBNY/Equifax CCP
Risk Score	Equifax Risk Score	FRBNY/Equifax CCP
Subprime Dummy	Indicator equal to 1 if household's risk score is less than 620	FRBNY/Equifax CCP
Log Income	Log of county-level quarterly total wages	BLS
Panel C: Syndicated Loans		
Nonbank	Indicator variable equal to one for nonbank lenders and zero for bank lenders	Thomson Reuters LPC DealScan
Nonbank relation	Indicator variable equal to one for borrowers who have previously borrowed from a nonbank (excluding loans in the previous two years)	Thomson Reuters LPC DealScan
Nonbank amount	Log of total credit extended to a borrower in a quarter from nonbanks	Thomson Reuters LPC DealScan
Bank amount	Log of total credit extended to a borrower in a quarter from banks	Thomson Reuters LPC DealScan
Nonbank share	Log of the ratio of total credit extended from nonbanks to total credit extended from all lenders	Thomson Reuters LPC DealScan
All loans	Log of total credit extended to a borrower in a quarter	Thomson Reuters LPC DealScan
Term loans	Log of total term loan amount extended to a borrower in a quarter	Thomson Reuters LPC DealScan
Revolvers	Log of total credit line amount extended to a borrower in a quarter	Thomson Reuters LPC DealScan
Borrowing	Log of total credit extended to a borrower in a quarter	Thomson Reuters LPC DealScan
Total debt	Log of total debt net of cash (dlcq + dlttq - cheq)	Compustat
Leverage	Log of book leverage net of cash ((dlcq + dlttq - cheq) / atq)	Compustat
Liquid asset ratio	Log of ratio of cash and short term investments to total assets (cheq / atq)	Compustat
PPE / Assets	Log of ratio of property, plant and equipment to total assets (ppentq / atq)	Compustat
High yield	Indicator variable equal to one if the borrower has a high yield credit rating, and equal to zero if it has an investment grade credit rating (splticrm)	Compustat
Log(borrower assets)	Log of lagged total assets (at)	Compustat

Nonbank Indentifican in HDMA

The identification of nonbanks in the HMDA data adapts the identification method used in Buchak et al. (2018a). There are four steps in the process, which begins by assuming that all lenders are nonbanks and then re-classifying them into banks where appropriate. A lender is classified as a bank if it meets at least one of the following criteria below. A lender that fails to meet any of the criteria remains classified as a nonbank. The order in which these steps are presented are the same as they appear in the algorithm.

The first step utilizes the lenders regulator. All lenders regulated by the following agencies are classified as banks; OCC, FDIC, OTS, NCUA, and CFPB. This methodology includes the lenders who filed to the state. In Buchak et al. (2018a) there are just 5 individual lenders that violate this classification, which are addressed in the fourth step.

Second, classifying lenders regulated by the Federal Reserve System is done using text analysis of the lenders name. Lenders regulated by the Federal Reserve with the following strings in their name are classified as banks; BANK, BK, BANCO, BANC, B&T, BNK. These strings are not case sensitive. Lenders regulated by the Federal Reserve without these strings remain classified as nonbanks.

Third, any bank identified as a Bank, Savings Association, or Credit Union or a Mortgage Banking Subsidiary of a Community Bank are classified as a bank. This is done using HMDAs OTHER_LENDER_CODE variable.

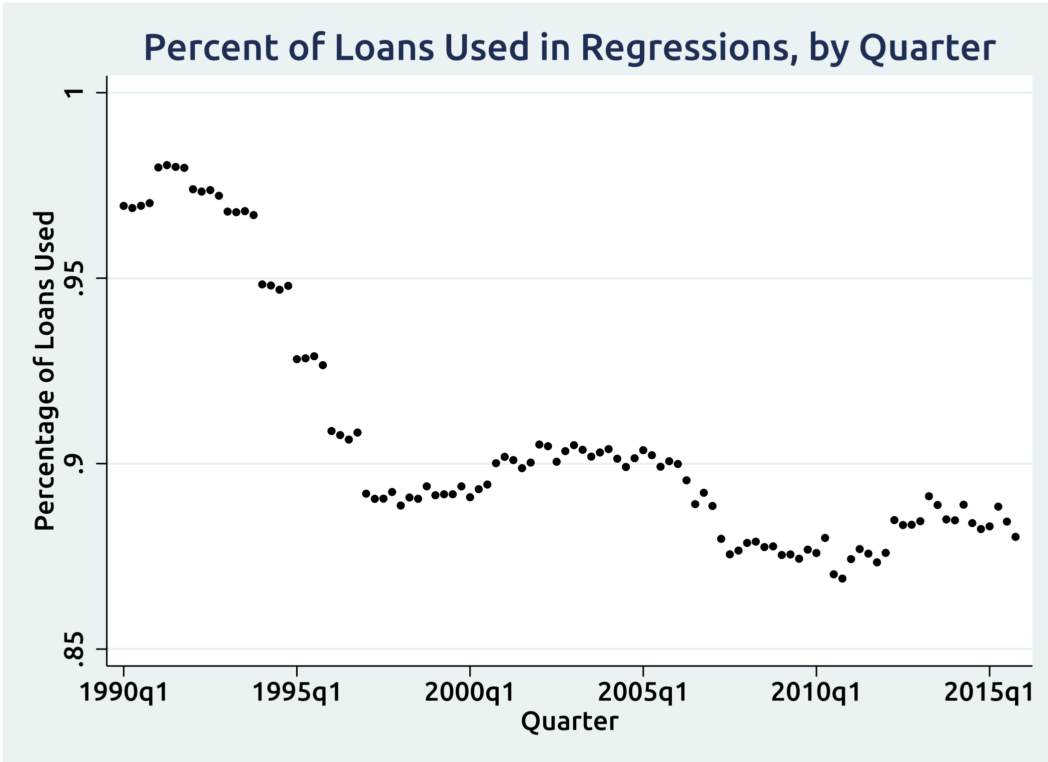
Finally, the method identifies the five one-off lenders consistent with the one-offs in Buchak et al. (2018a). The following are classified as nonbanks despite their regulator; Merrimack Mortgage Company (FDIC) and Suntrust Mortgage (CFPB). The following are classified as banks despite being regulated by HUD; Homeowners Mortgage Company, Liberty Mortgage Corporation, and Prosperity Mortgage Company.

Table A1
Nonbanks by regulator

This tables shows the result of the classification algorithm.

HDMA Regulator Code	Share Bank
1 - OCC	100%
2 - FRS	53.7%
3 - FDIC	99.98%
4 - OTS	100%
5 - NCUA	100%
7 - HUD	0.06%
8 - PMIC	0%
9 - CFPB	97.17%

Figure A1: Percent of HMDA Loans Included in the Sample



Appendix B: Robustness Tests

In Table B1 show results of estimating equation 2 for non-U.S. borrowers. In these specifications we also employ borrower-month fixed effects that implicitly control for the borrower's home country monetary policy and macroeconomic conditions. In this sample, we also find that nonbanks expand credit supply to non-U.S. borrowers in response to a monetary policy shock when compared to their bank peers for the same borrower. The estimated effect are in magnitude comparable to n the effects on U.S. borrowers. However, we do not find any additional effect for nonbanks with fragile funding.

Table B1
Impact of US monetary policy on non-US corporate lending

The table shows estimated regression coefficients for equation 2. The dependent variable is the log of lending quantity from DealScan. Only observations where lender shares are observed are included. GK refers to lagged cumulative sums of the monetary policy shocks of Gertler and Karadi (2015) for the US. The regressions are at quarterly frequency. The sample period is 1990-2012. The sample consists of dollar-denominated loans where the borrower country is not the USA. Standard errors clustered by borrower, lender and month. All variables are defined in Appendix A.

	Total Lending (1)	Term Loans (2)	Revolvers (3)	Total Lending (4)	Term Loans (5)	Revolvers (6)
Nonbank x GK	0.269***	0.221***	0.0823	-0.0229	0.257**	0.0704
	(0.0536)	(0.0773)	(0.0544)	(0.108)	(0.112)	(0.135)
Nonbank x VIX	-0.00363	-0.00142	-0.00380	0.00608	-0.00833	0.00666
	(0.00340)	(0.00457)	(0.00690)	(0.00772)	(0.00755)	(0.0136)
Nonbank x Inflation	0.00520	0.0458**	-0.0185	0.00459	-0.0234	-0.132
	(0.0205)	(0.0205)	(0.0367)	(0.0490)	(0.0309)	(0.0853)
Nonbank x GDP	0.00611	0.00657	0.00993	0.000554	0.00280	0.0268
	(0.00677)	(0.00756)	(0.0164)	(0.0131)	(0.0164)	(0.0220)
Nonbank x GDP forecast	-0.0496	-0.0312	-0.0365	-0.00268	-0.0349	0.000485
	(0.0301)	(0.0343)	(0.0440)	(0.0420)	(0.0499)	(0.0839)
Quarter FEs	-	-	-	Yes	Yes	Yes
Borrower-quarter FEs	Yes	Yes	Yes	No	No	No
Lender FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	62561	31408	10907	63425	31964	11050
Number of borrowers	4789	3230	955	5364	3658	1074
Number of lenders	2841	2120	996	2870	2139	1002
Number of quarters	90	89	87	90	89	88
R-squared	0.867	0.866	0.921	0.475	0.494	0.505

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B2
Aggregate Syndicated Loans: Substitution - Robustness

The table shows estimated regression coefficients for equation 1. The dependent variable is the log share of nonbanks in syndicates. Only observations where lender shares are observed are included. GK refers to lagged cumulative sums of the monetary policy shocks of Gertler and Karadi (2015) for the US. The regressions are at quarterly frequency. In columns 1-3, the sample period is 1990-2012. The sample consists of dollar-denominated loans where the borrower country is the USA. Column 1 includes time-varying borrower-level controls. Column 2 includes borrower fixed effects. Column 3 estimates the equation using weighted least squares (WLS), with the weights provided by the log of borrower total assets. Columns 4 and 5 replace GK with the Fed Funds target rate or Wu-Xia shadow rate, respectively. For these columns, the sample period is 1990-2017. Column 6 restricts the sample period to 1990-2006. Standard errors clustered by borrower and quarter. All variables are defined in Appendix A.

	Nonbank Share					
	(1)	(2)	(3)	(4)	(5)	(6)
	Firm controls	Firm FE	WLS	Fed Funds	Wu-Xia	Pre-crisis
Gertler-Karadi sum	0.131**	0.265***	0.545***			0.568***
	(0.0649)	(0.0553)	(0.0380)			(0.0389)
Fed Funds				0.143***		
				(0.0154)		
Wu-Xia					0.129***	
					(0.0123)	
VIX	0.00428	-0.00421	-0.0153**	-0.00752	-0.0109*	-0.0201**
	(0.00647)	(0.00482)	(0.00727)	(0.00643)	(0.00625)	(0.00765)
Inflation	0.0492	0.0132	-0.0470	0.0267	0.0284	-0.0987***
	(0.0408)	(0.0301)	(0.0320)	(0.0356)	(0.0345)	(0.0360)
GDP growth	-0.00898	-0.0301*	-0.0100	0.00642	0.00646	0.0126
	(0.0183)	(0.0156)	(0.0178)	(0.0202)	(0.0196)	(0.0177)
GDP growth forecast	0.0598	0.0757*	0.0170	0.0616	0.0395	0.0319
	(0.0485)	(0.0450)	(0.0522)	(0.0667)	(0.0621)	(0.0488)
High yield borrower	0.513***					
	(0.0862)					
Log(Borrower assets)	-0.141***					
	(0.0273)					
Industry FEs	Yes	No	Yes	Yes	Yes	Yes
Borrower FEs	No	Yes	No	No	No	No
Observations	1800	2355	3699	5824	5824	4031
Number of borrowers	1029	882	2463	4068	4068	2978
Number of quarters	90	90	90	112	112	67
R-squared	0.384	0.722	0.355	0.314	0.320	0.367

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B3
County-Level Effects - Number of Loans

This table shows the regression results of equation 6. The dependent variable is the log of the number of new loans extended by finance companies (columns 1, 4, 7), the log of the number of new loans extended by banks (columns 2, 5, 8), or the log of the number of all new loans (column 3, 6, 9). Columns 4-6 show results for counties with an average credit score above the median across all counties. Columns 7-9 show results for counties with an average credit score above the median across all counties. The sample period is from 1999 to 2012. Standard errors are clustered by quarter and county. All variables are defined in Appendix A.

	Log New Loans								
	All Counties			Below Median Risk Score Counties			Above Median Risk Score Counties		
	Nonbank	Bank	Total	Nonbank	Bank	Total	Nonbank	Bank	Total
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GK x Nonbank Share 1999	0.0673***	-0.0799***	-0.00596	0.0704***	-0.0983***	-0.0137	0.0513***	-0.0782***	-0.0201
	(0.0128)	(0.0173)	(0.0171)	(0.0187)	(0.0183)	(0.0238)	(0.0151)	(0.0233)	(0.0196)
GDP x Nonbank Share 1999	0.00341*	-0.000989	0.00348	0.00348	-0.000754	0.00330	0.00411	-0.00192	0.00318
	(0.00200)	(0.00330)	(0.00245)	(0.00277)	(0.00352)	(0.00324)	(0.00248)	(0.00373)	(0.00307)
Inflation x Nonbank Share 1999	-0.00141	0.00701	0.00465	-0.00211	0.00548	0.00181	-0.00249	0.00326	0.00222
	(0.00316)	(0.00483)	(0.00304)	(0.00473)	(0.00637)	(0.00497)	(0.00440)	(0.00415)	(0.00494)
VIX x Nonbank Share 1999	0.00260***	-0.00140	0.000720	0.000702	-0.00183	-0.000575	0.00407***	-0.000825	0.00172
	(0.000803)	(0.00149)	(0.00137)	(0.00140)	(0.00178)	(0.00204)	(0.001000)	(0.00136)	(0.00109)
GDP Forecast x Nonbank Share 1999	0.00810	-0.00541	0.00145	0.000000244	-0.00853	-0.00387	0.0137**	0.00265	0.00803
	(0.00584)	(0.00944)	(0.00913)	(0.00925)	(0.00940)	(0.0117)	(0.00675)	(0.0112)	(0.00823)
Time-varying County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	158,461	158,461	158,461	86,270	86,270	86,270	72,059	72,059	72,059
R^2	0.787	0.749	0.826	0.769	0.729	0.810	0.812	0.771	0.846

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B4
County-Level Effects on Auto Loans

This table shows the regression results of equation 6. The dependent variable is the log of new auto loans extended by finance companies (columns 1, 4), the log of new auto loans extended by banks (columns 2, 5), or the log of all new auto loans (column 3, 6). Columns 1-3 show results for counties with an average credit score below the 25th percentile across all counties. Columns 4-6 show results for counties with an average credit score above lowest quartile across all counties. The sample period is from 1999 to 2012. Standard errors are clustered by quarter and county. All variables are defined in Appendix A.

	Log New Loan Amounts					
	Riskiest Loans			Less Risky Loans		
	Nonbank	Bank	Total	Nonbank	Bank	Total
	(1)	(2)	(3)	(4)	(5)	(6)
GK x Nonbank Share 1999	0.109	-0.394**	-0.0329	0.581***	-0.743***	0.0574
	(0.261)	(0.196)	(0.237)	(0.0853)	(0.161)	(0.113)
GDP x Nonbank Share 1999	0.0506	-0.00709	0.0500	0.0234	-0.0134	0.0248
	(0.0513)	(0.0351)	(0.0493)	(0.0167)	(0.0246)	(0.0206)
Inflation x Nonbank Share 1999	0.0384	-0.0498	0.00154	-0.0449	0.0721***	0.0195
	(0.0654)	(0.0567)	(0.0574)	(0.0291)	(0.0262)	(0.0379)
VIX x Nonbank Share 1999	0.0316*	-0.0151	0.0258	0.0211***	-0.0185*	-0.00359
	(0.0168)	(0.0145)	(0.0161)	(0.00454)	(0.0106)	(0.00827)
GDP Forecast x Nonbank Share 1999	0.161	-0.110	0.0682	0.0535	-0.0591	-0.0392
	(0.106)	(0.0865)	(0.111)	(0.0361)	(0.0826)	(0.0588)
Lagged Risk Score	-0.00332	0.00344	-0.000465	-0.00389***	-0.00136	-0.00418***
	(0.00238)	(0.00243)	(0.00258)	(0.00132)	(0.00139)	(0.00135)
County-Level Income	0.769***	0.852***	1.033***	0.645***	0.528***	0.660***
	(0.214)	(0.192)	(0.206)	(0.103)	(0.0902)	(0.110)
Time FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Observations	39,500	39,500	39,500	118,858	118,858	118,858
R^2	0.431	0.428	0.444	0.513	0.503	0.526

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B5
County-Level Effects on Auto Loan Market Share

This table shows the regression results of equation 6. The dependent variable is the finance companies' county-level market share measured as share of new loan amounts (columns 1-3) or the finance companies' county-level market share measured as share of new loans (columns 4-6). Columns 2 and 5 show results for counties with an average credit score above the median across all counties. Columns 3 and 6 show results for counties with an average credit score above the median across all counties. The sample period is from 1999 to 2012. Standard errors are clustered by quarter and county. All variables are defined in Appendix A.

	All Counties	Above Median Score	Below Median Score	All Counties	Above Median Score	Below Median Score
		Market Share Amount			Market Share Loans	
	(1)	(2)	(3)	(4)	(5)	(6)
GK x Nonbank Share 1999	0.0654***	0.0741***	0.0597***	0.0699***	0.0612***	0.0799***
	(0.00984)	(0.0140)	(0.0132)	(0.00985)	(0.0136)	(0.0142)
GDP x Nonbank Share 1999	0.00328*	0.00377	0.00299	0.00283	0.00342	0.00266
	(0.00172)	(0.00252)	(0.00227)	(0.00174)	(0.00235)	(0.00254)
Inflation x Nonbank Share 1999	-0.00349	-0.00471	-0.00200	-0.00346	-0.00190	-0.00468
	(0.00393)	(0.00555)	(0.00380)	(0.00401)	(0.00364)	(0.00572)
VIX x Nonbank Share 1999	0.00228***	0.00141	0.00284***	0.00219***	0.00249***	0.00146
	(0.000494)	(0.000891)	(0.000731)	(0.000585)	(0.000797)	(0.000982)
GDP Forecast x Nonbank Share 1999	0.00873**	0.00587	0.00956	0.00843*	0.00602	0.00795
	(0.00401)	(0.00653)	(0.00611)	(0.00450)	(0.00708)	(0.00726)
Lagged Risk Score	-0.000351***	-0.000250	-0.000359**	-0.000397***	-0.000395***	-0.000294*
	(0.000102)	(0.000159)	(0.000139)	(0.000104)	(0.000138)	(0.000155)
County-Level Income	0.0276***	0.00768	0.0455***	0.0291***	0.0448***	0.0117
	(0.00885)	(0.0132)	(0.0103)	(0.00846)	(0.0102)	(0.0130)
County FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Observations	158,461	86,270	72,059	158,461	72,059	86,270
R^2	0.205	0.188	0.225	0.215	0.234	0.197

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B6
County-Level Effects - Weighted Regressions

This table shows the regression results of equation 6. The dependent variable is the log of new auto loans extended by finance companies (columns 1, 4), the log of new auto loans extended by banks (columns 2, 5), or the log of all new auto loans (column 3, 6). Columns 1-3 show results for counties with an average credit score above the median across all counties. Columns 4-6 show results for counties with an average credit score in the median across all counties. Observations are weighted with lagged total auto loan balances. The sample period is from 1999 to 2012. Standard errors are clustered by quarter and county. All variables are defined in Appendix A.

	Log New Loan Amount					
	Below Median Risk Score Counties			Above Median Risk Score Counties		
	Nonbank	Bank	Total	Nonbank	Bank	Total
	(1)	(2)	(3)	(4)	(5)	(6)
GK x Nonbank Share 1999	0.184	-0.332*	0.0696	0.333*	-0.445**	0.178
	(0.195)	(0.166)	(0.0984)	(0.193)	(0.167)	(0.107)
GDP x Nonbank Share 1999	0.00462	0.00464	0.0171	0.0230	0.00995	0.0200
	(0.0420)	(0.0224)	(0.0148)	(0.0355)	(0.0292)	(0.0167)
Inflation x Nonbank Share 1999	-0.0134	0.0141	-0.0148	-0.0499	0.0588	-0.00711
	(0.0884)	(0.0246)	(0.0250)	(0.0488)	(0.0451)	(0.0243)
VIX x Nonbank Share 1999	0.0431***	0.00259	0.0195***	0.00238	-0.00216	0.000934
	(0.0140)	(0.00844)	(0.00493)	(0.0130)	(0.0131)	(0.00774)
GDP Forecast x Nonbank Share 1999	-0.0309	0.0122	0.0519	-0.124	-0.128	-0.0875
	(0.158)	(0.0702)	(0.0501)	(0.106)	(0.0835)	(0.0594)
Lagged Risk Score	-0.00360	-0.00110	-0.00239	-0.00482*	0.00160	-0.00176
	(0.00262)	(0.00250)	(0.00191)	(0.00266)	(0.00266)	(0.00196)
County-Level Income	0.806***	0.414***	0.477***	0.757***	0.866***	0.719***
	(0.142)	(0.123)	(0.0854)	(0.130)	(0.156)	(0.0936)
Time FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Observations	70,786	70,786	70,786	85,428	85,428	85,428
R^2	0.637	0.602	0.668	0.628	0.615	0.658

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B7
County-Level Effects Dependency vs HHI

This table shows the regression results of equation 6. The dependent variable is the log amount of new auto loans extended by nonbanks (column 1) or by banks (column 2), log number of new auto loans extended by nonbanks (column 3)or by banks (column 4), or market share of nonbanks (columns 5 and 6). The sample period is from 1999 to 2012. Standard errors are clustered by quarter and county. All variables are defined in Appendix A.

	Log Loan Amount		Log Loans		Market Share	
	Nonbank	Bank	Nonbank	Bank	(Amount)	(Loans)
	(1)	(2)	(3)	(4)	(5)	(6)
GK x Nonbank Share 1999	0.501***	-0.595***	0.0654***	-0.0816***	0.0697***	0.0649***
	(0.102)	(0.117)	(0.0127)	(0.0172)	(0.00992)	(0.00989)
HHI x GK	-0.00671	0.390***	-0.123*	-0.0350	-0.0108	-0.0373**
	(0.180)	(0.142)	(0.0651)	(0.0423)	(0.0169)	(0.0173)
GDP x Nonbank Share 1999	0.0161	-0.0125	0.00289	-0.000804	0.00250	0.00297*
	(0.0187)	(0.0219)	(0.00199)	(0.00332)	(0.00174)	(0.00172)
Inflation x Nonbank Share 1999	-0.0264	0.0570**	-0.00146	0.00729	-0.00360	-0.00363
	(0.0341)	(0.0245)	(0.00304)	(0.00500)	(0.00401)	(0.00392)
VIX x Nonbank Share 1999	0.0218***	-0.0196*	0.00259***	-0.00141	0.00220***	0.00230***
	(0.00615)	(0.0106)	(0.000809)	(0.00152)	(0.000587)	(0.000496)
GDP Forecast x Nonbank Share 1999	0.0843	-0.0881	0.00776	-0.00627	0.00903**	0.00934**
	(0.0505)	(0.0706)	(0.00599)	(0.00960)	(0.00448)	(0.00401)
HHI x VIX	0.00546	-0.0250***	-0.000419	-0.00219	0.0000324	0.000685
	(0.0105)	(0.00838)	(0.00445)	(0.00361)	(0.00116)	(0.00121)
HHI x Inflation	-0.0163	0.0496	-0.0000336	0.0260	-0.00686	-0.00761
	(0.0538)	(0.0609)	(0.0221)	(0.0219)	(0.00627)	(0.00648)
HHI x GDP	-0.110***	0.00758	-0.0284**	0.0138*	-0.0163***	-0.0156***
	(0.0277)	(0.0221)	(0.0124)	(0.00804)	(0.00250)	(0.00287)
HHI x GDP Forecast	0.0887	-0.237***	-0.0293	-0.0766**	0.0267***	0.0292***
	(0.0831)	(0.0649)	(0.0432)	(0.0316)	(0.00799)	(0.00883)
Lagged Risk Score	-0.00409***	-0.000400	-0.000343***	0.0000718	-0.000411***	-0.000376***
	(0.00100)	(0.00124)	(0.000113)	(0.000156)	(0.000103)	(0.000102)
County-Level Income	0.687***	0.660***	0.0611***	0.0889***	0.0287***	0.0268***
	(0.0874)	(0.0846)	(0.0125)	(0.0127)	(0.00838)	(0.00879)
Lagged HHI	-0.0690	0.734*	-0.0725	-0.0846	0.0243	-0.00332
	(0.435)	(0.387)	(0.135)	(0.112)	(0.0484)	(0.0511)
County FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Observations	157,981	157,981	157,981	157,981	157,981	157,981
R^2	0.488	0.489	0.787	0.749	0.214	0.204

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B8
Robustness: Dependence and Market Share of Nonbanks—Crisis

Market share is calculated as the value of loans compared to the total value of all loans issued in each county-quarter cell. Date Range: 1990q2 - 2012q3. All counties issued at least 10 loans in every quarter prior to 2008. GK, the MP Shock, is the cumulative sum of monerary policy shocks of Gertler and Karadi (2015). Crisis is a dummy equal to one in for the period 2007Q1-2009Q4. All lagged variables are on a one quarter lag. Observations weighted with lagged county-level income. Standard errors are clustered on the county-level.

Panel A: Crisis as Control								
	Conforming Loans				Jumbo Loans			
	Bank	Nonbank	All	Nonbank Share	Bank	Nonbank	All	Nonbank Share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1990 Nonbank Share x GK	-0.481***	0.875***	-0.143***	0.0151***	-0.493***	0.256	-0.104	0.129***
	(0.093)	(0.158)	(0.051)	(0.018)	(0.157)	(0.229)	(0.143)	(0.015)
1990 Nonbank Share x Crisis	-0.0918	0.405	-0.067	0.023	0.097	-1.029	0.174	-0.0843***
	(0.087)	(0.277)	(0.044)	(0.040)	(0.203)	(0.682)	(0.203)	(0.030)
Macro Variables x 1990 Nonbank Share	yes	yes	yes	yes	yes	yes	yes	yes
County FE	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	76,451	76,451	76,451	76,451	76,451	76,451	76,451	76,451
Adjusted R^2	0.91	0.90	0.95	0.69	0.71	0.73	0.73	0.35

Panel B: Crisis Interaction								
	Conforming Loans				Jumbo Loans			
	Bank	Nonbank	All	Nonbank Share	Bank	Nonbank	All	Nonbank Share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1990 Nonbank Share x GK x Crisis	0.0846	-0.583***	0.0553	-0.042	-0.062	1.585**	-0.057	0.121***
	(0.089)	(0.187)	(0.046)	(0.034)	(0.242)	(0.644)	(0.233)	(0.028)
1990 Nonbank Share x GK	-0.474***	0.780***	-0.144***	0.143***	-0.540***	0.256	-0.147	0.134***
	(0.094)	(0.124)	(0.052)	(0.017)	(0.162)	(0.252)	(0.147)	(0.016)
Triple Interactions	yes	yes	yes	yes	yes	yes	yes	yes
Double Interactions	yes	yes	yes	yes	yes	yes	yes	yes
County FE	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	76,451	76,451	76,451	76,451	76,451	76,451	76,451	76,451
Adjusted R^2	0.91	0.90	0.95	0.70	0.71	0.73	0.73	0.35
Quarters	89	89	89	89	89	89	89	89
Counties	860	860	860	860	860	860	860	860

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$